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Review

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Integrating artificial intelligence in the lifecycle evolution of district heating networks: challenges and opportunities

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Abstract: The evolution of next-generation district heating networks toward higher efficiency and sustainability is constrained by persistent challenges in supply–demand coordination and lifecycle optimization. This paper provides a comprehensive review of artificial intelligence (AI) integration across four key lifecycle stages of heating networks: planning and design, construction and renewal, operation and control, and maintenance and fault diagnosis. Critical research gaps are identified, including application fragmentation and persistent data silos. Existing literature has demonstrated that AI-based approaches can deliver significant performance improvements across multiple lifecycle stages. In the planning phase, AI can improve design computational efficiency, in some cases by up to an order of magnitude. In the construction phase, AI-enhanced management has been shown to accelerate project timelines while reducing costs. For operational control, deep learning models can reduce thermal load forecasting errors by more than half. In the maintenance stage, AI enables multi-day early fault warnings with localization accuracies exceeding 95% in representative studies. To address the limitation of fragmented applications, a digital thread framework is proposed to enable cross-lifecycle data continuity and integration of decision-making across engineering stages. Finally, future research directions are outlined, emphasizing adaptive AI frameworks aligned with urban evolution, integration of digital twins with intelligent optimization agents, and the development of interpretable and transferable AI models.

Key words: District heating network; Artificial intelligence; Lifecycle; Digital thread

1 Introduction

The global energy transition, as driven by the need to mitigate climate change and promote urban sustainability, has led to redesigning of energy infrastructure (Luderer et al., 2022). Broadly defined, energy systems encompass the generation, transmission, distribution, and consumption of energy across various sectors, including electricity, heating, and transportation (Wu et al., 2025). Heating demand currently accounts for approximately 50% of global energy consumption and generates 37% of energy-related CO_2 emissions (Iea, 2025). In China, coal accounted for 62% of the primary energy consumption in 2023, and fossil fuels still provided 63% of electricity generation in 2024 (Eia, 2024). Within this framework, district heating networks (DHN) serve as a critical component of urban energy infrastructure, providing reliable and centralized heat supply to residential, commercial, and industrial buildings.

Over the past few decades, many DHN – particularly in regions like northern Europe and China

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– have heavily relied on large-scale, often coal-fired, power plants or dedicated boilers for heat generation. While effective at meeting base-load heating demands, this traditional model faces increasing pressure from several converging factors (Lund et al., 2025).

First, mitigating climate change necessitates a diversified, fundamental shift towards decarbonization (Lin et al., 2026), as evidenced by record global energy-related CO_2 emissions of 37.8 Gt in 2024, with the Chinese power sector accounting for over 5.6 Gt alone (Iea, 2025). Second, air quality concerns in urban areas are driving replacement of polluting coal-fired boilers with long-distance large heating alternatives (Meibodi and Loveridge, 2022; Guelpa et al., 2023). Third, the growing penetration of renewable energy sources – such as geothermal, solar thermal, and waste heat recovery – presents both challenges and opportunities for integrating these variable, often lower-temperature heat sources into existing DHN infrastructures (Zhang et al., 2022). Traditionally, their operation, planning, and maintenance have relied on physics-based models and expert-driven heuristics. All the factors above point to the need for a profound transformation of DHN, moving beyond simple fuel substitution towards more holistic solutions – for example involving upgrades to network components, redesign of operational strategies, and enhanced integration of diverse heat sources. Such a transition aims to improve energy efficiency, reduce carbon emissions, enhance system flexibility, and ensure long-term economic viability.

To navigate this complex transition, artificial intelligence (AI) technologies have emerged with the potential to significantly accelerate and optimize the transformation of DHN across their entire lifecycles. Importantly, AI is not a monolithic technology but a spectrum of methodologies, each offering distinct advantages for different DHN lifecycle stages, as summarized in

Table 1.

Machine learning (ML), such as the support vector machine (SVM) and XGBoost (XGB) methods, excels at extracting patterns from structured historical data; as such, it offers high computational efficiency for tasks like load forecasting (Lin et al., 2026) and leakage detection (Xue et al., 2019). AI models deployed in district heating systems (e.g., XGB, LSTM-TCN) have achieved MAPE as low as 2.47%, leading to operational cost savings and improved load balancing (Song et al., 2024).

Table 1 AI Technologies for DHN: principles, advantages, and techniques

AI	Principle	Advantages	Technologies	Reference
Machine Learning	Statistical induction from data patterns	Efficient; robust on limited data	SVR, XGBoost, KNN, Random Forest	Zhou et al. (2024)
Deep Learning	Hierarchical representation via multi-layer networks	Auto-feature extraction; spatiotemporal data	CNN, LSTM, Transformers, Informer, PINN	Chen et al. (2025)
Reinforcement Learning	Reward-based interaction and policy learning	Autonomous real-time optimization	DDPG, SAC, PPO, DQN, SARSA	Elhafaia et al. (2025)
Evolutionary Algorithms	Bio-inspired population-based stochastic search	Non-convex spaces without gradients	Genetic Algorithms, PSO, ACO, Simulated Annealing	Chan (2024)
Multi-Agent Systems	Distributed negotiation and coordination	Decentralized coordination	Collaborative MAS, MARL	Mazzarino et al. (2022)
Expert Systems / NLP	Symbolic reasoning and semantic analysis	Automates text-based engineering	LLMs, BERT, Case-based reasoning, Rule-based matching	Souza et al. (2025)

Deep learning – including models such as Convolutional Neural Networks (CNN) and Transformers – utilizes multi-layered architectures to process unstructured data (e.g., thermal imagery for anomaly detection) (Vollmer et al., 2025) and capture complex temporal dependencies in long-term sequence prediction (Zhou et al., 2021). Physics-Informed Neural Networks (PINNs) represent a hybrid paradigm that integrates established physical laws—such as pipe heat balance and thermodynamics—directly into the neural network architecture or loss function (De Giuli et al., 2024). Related hybrid architectures, including CNN–LSTM models augmented with synthetic data, have achieved strong fault detection performance in both laboratory and real-world conditions, with reported F1-scores of approximately 0.95 and 0.92, respectively (Van Dreven et al., 2025).

Reinforcement learning (RL) represents a shift from simple prediction to autonomous decision-making. By learning through interaction, RL agents (e.g., DDPG) are particularly adept at optimizing real-time control strategies in dynamic multi-vector energy systems where traditional physical models may fall short (Elhafaia et al., 2025). Building on this autonomy, multi-agent systems (MAS) provide the organizational structure for decentralized DHN. By treating individual heat substations and prosumers as autonomous agents, MAS enables peer-to-peer energy trading and collaborative load balancing; this ensures system-wide stability through local negotiations rather than vulnerable centralized commands.

Evolutionary algorithms (EA) are a core branch of AI focused on population-based stochastic search, as inspired by natural selection. Expert systems and natural language processing (NLP) rely on knowledge bases and semantic analysis to handle deterministic tasks, such as compliance checking and contract risk assessment during the engineering phases (Dikmen et al., 2025b). As research on AI techniques matures, their scope of application within DHN is continuously broadening, essentially touching on every stage from initial planning and design, through construction and renewal, to ongoing operation, control, and maintenance.

Several review articles have already explored the intersection of AI and DHN, as summarized in Table 2. For example, Mbiydzenyuy et al. (2021) focused on load forecasting algorithms and the evolution of technical/business logic, but largely omitted the construction and renewal phases of heating infrastructure. Moreover, Buffa et al. (2021) provided an in-depth analysis of advanced control and fault detection in 4G/5G systems.

Table 2 Comparison of existing review articles on AI and digitalization in DHN

Reference	PD	CR	OC	MD	Core Focus & Research Gap
Mbiydzenyuy et al. (2021)	☐	☐	☑	☐	Focused on ML load forecasting; explicitly omitted construction
Buffa et al. (2021)	☐	☐	☑	☑	4G/5G control and FDD; scope was confined to operational phase
Zhang et al. (2024b)	☐	☐	☑	☐	Focuses on 5G DHN temperature curves; lacked lifecycle data flow analysis
Ntakolia et al. (2022)	☑	☐	☑	☐	ML technology and governance; lacked engineering implementation
Brown et al. (2022)	☑	☐	☐	☐	Modeling approaches; focused on principles rather than evolution
Kuntuarova et al. (2024)	☑	☐	☐	☐	Model validation lacked standardized real-world testing
Rafati and Shaker (2024)	☐	☐	☐	☑	Predictive maintenance; lacked a design-maintenance feedback loop
Gjoka et al. (2023)	☑	☐	☑	☐	5G DHN performance; scarce design guidelines and data integration
Jiang et al. (2022)	☑	☐	☐	☐	Optimal planning; insufficient discussion on dynamic evolution
Zhou et al. (2024)	☑	☐	☑	☐	Energy sharing in carbon-neutral districts; lacked construction analysis
This Work	☑	☑	☑	☑	**Full lifecycle perspective & Digital thread framework**

Note: PD = Planning and design; CR = Construction and renewal; OC = Operation and control; MD = Maintenance and fault diagnosis.

However, their scopes were largely confined to the operational phase, overlooking the impact of early-stage design decisions on long-term maintenance. Zhang et al. (2024b) reviewed temperature control strategies for 5G DHN systems using virtual testbeds, but lacked a systematic discussion of how data flows across different lifecycle stages. Complementing these observations, Ntakolia et al. (2022) mapped ML applications to governance layers, but provided limited insights into the granular engineering implementation details required for field deployment. Brown et al. (2022) systematically reviewed modeling tools and simulation strategies, although their focus on mathematical principles tended to bypass the dynamic evolution and construction risks inherent in aging networks. Finally, while Rafati and Shaker (2024) advanced the field of predictive maintenance (PdM), their analysis treated the maintenance phase as an isolated event, and thus lacked a robust feedback loop to optimize early-stage planning and design.

Collectively, these studies emphasize technical optimization in isolated stages, leaving the engineering construction phase and systemic cross-lifecycle data synergy as significant research gaps. Since the transition of DHN is a complex system-wide process, it is vital to systematically map the diverse applications of AI across the entire lifecycle of DHN transformation. A comprehensive review is essential for highlighting the unique challenges and opportunities at each stage.

Accordingly, in this review we aim to fill this gap by providing a holistic perspective on the role of AI technologies in supporting the transformation of DHN throughout their complete lifecycles. The goal is to systematically identify, categorize, and discuss state-of-the-art AI applications in each key lifecycle stage: planning and design, construction and retrofitting, operation and control, and maintenance and fault diagnosis. By doing so, we seek to answer the following questions:

(1) How can AI technologies be effectively integrated into each distinct phase of the DHN lifecycle to address the specific challenges posed by the energy transition?

(2) What are the unique opportunities and gaps for AI applications at different lifecycle stages?

(3) How can the insights gained from AI applications in one stage inform and optimize processes in subsequent phases, fostering more cohesive and intelligent DHN ecosystems?

This overview is intended to provide researchers and practitioners with a clear understanding of the current landscape, identify future research directions, and support the successful, efficient, and sustainable transformation of DHN.

The remainder of this review is organized as follows: Section 2 introduces the broader context of the energy system transition and provides an overview of DHN transformation across lifecycle stages. It also summarizes common AI techniques frequently applied towards this end. Section 3 discusses how AI can be integrated into each transformation, namely planning and design, construction and renewal, operation and control, and maintenance and fault diagnosis. Section 4 reviews the current state-of-the-art approaches and identifies existing research gaps. Section 5 proposes a framework to support AI integration throughout the entire DHN lifecycle, ensuring consistent data flow and bridging the gaps between fragmented AI solutions. Finally, Section 6 presents the key findings.

2 Artificial intelligence and the DHN lifecycle

Energy systems – encompassing both the broader concept of energy infrastructure and the more specific domain of power systems – are undergoing a continuous and profound evolution. For instance, in the ERCOT market, an additional 1 GWh of wind energy generation reduces wholesale electricity prices by about 2.27 USD/MWh on average, while reported estimates across different regions range from 0.4 to 13 USD/MWh, reflecting strong system uncertainty and variability (Çolak and Irmak, 2023).

2.1 Evolution of power systems and low-carbon DHN

Power systems are also undergoing an unprecedented transformation (Castaneda et al., 2017). The large-scale integration of renewable energy sources has played a positive role in reducing carbon emissions. However, their inherent intermittency and uncertainty have also presented new challenges to stable power grid operations (Çolak and Irmak, 2023). Quantitative analyses have shown that uncertainties in wind generation can nearly double both marginal operating costs and the number of conventional generator start-ups compared to perfectly forecasted conditions. Moreover, reducing renewable forecasting errors to the level of demand uncertainty could lower system integration costs by approximately 0.5 million USD per year in representative electricity markets. Simultaneously, the rise of distributed generation poses challenges to traditional business models (Castaneda et al., 2017). Against this backdrop, the application of smart grid technologies using techniques such as artificial intelligence has become crucial.

As an integral part of power systems, DHN are undergoing a transformation due to challenges such as the energy transition, new technologies, and environmental concerns. Traditional district heating systems, which primarily rely on fossil fuels and operate at high temperatures, suffer from significant heat losses and are increasingly unable to meet the growing demand for low-carbon energy. To address these challenges, fifth-generation district heating networks (5GDHN) were developed (Fig. 1). The transformation to 5GDHN represents the forefront of the heating industry's response to the dual challenge of accelerating urbanization and climate change. Low-carbon 5GDHN features near-ambient temperature operation, bidirectional energy flow between users and producers, and decentralized heating (Gjoka et al., 2023). Unique developments have also emerged, such as the phasing-out of coal-fired boilers (Wu et al., 2024), the rise of long-distance waste-heat supply, and the operation of multi-source heating networks (Wang et al., 2019).

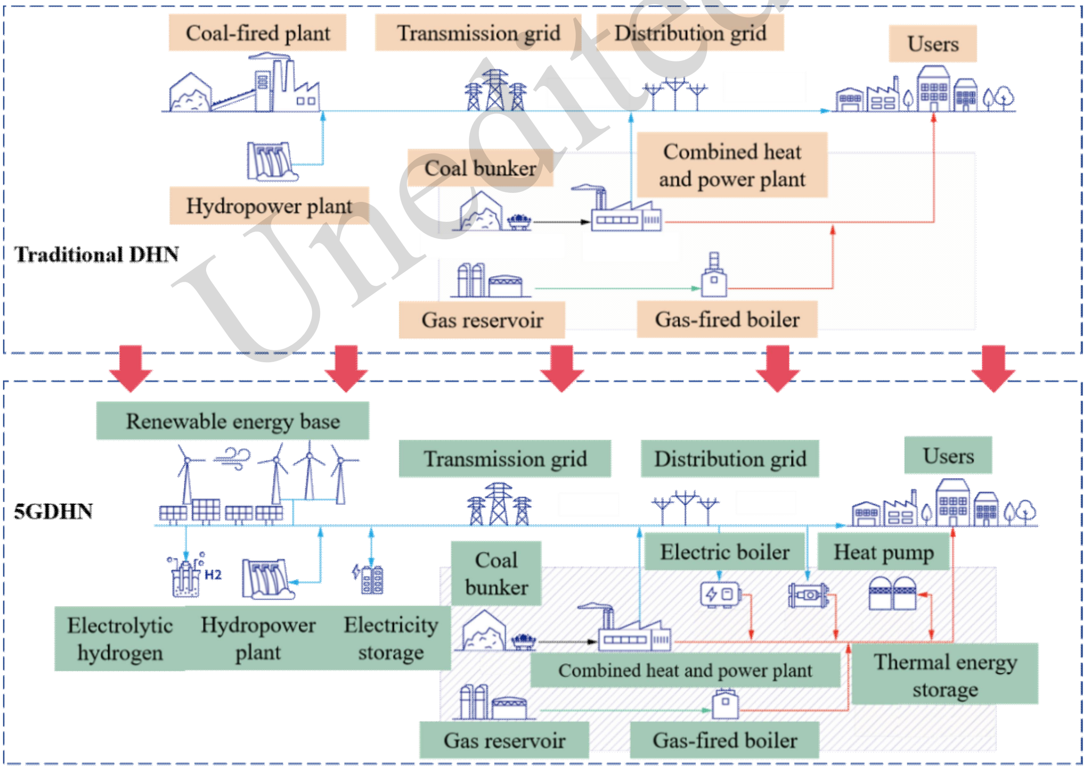

Fig. 1 From traditional DHN to 5GDHN

Existing literature has predominantly focused on individual transformation measures (Kleinertz and Gruber, 2022). To address this gap, we develop a comprehensive set of transformation strategies. As shown in Fig. 2, three core characteristics of the 5GDHN transformation are delineated: multi-sector coordination, multi-time evolution, and multi-space restructuring. 1) The multi-sector coordination encompasses both internal and external dimensions. Internally, it involves the collaboration of office automation systems across various departments within a heating enterprise. Externally, it necessitates procedural approvals and coordination between multiple municipal departments. 2) The multi-time scale evolution spans the entire lifecycle of a DHN throughout the transformation period, encompassing stages such as planning, construction, operation, and maintenance. 3) The multi-space scale restructuring primarily manifests in the upgrading and reconstruction of heating networks, and the transformation of heat sources (Johansen and Werner, 2022; Zhou et al., 2024).

The transformation of 5GDHN is characterized by its prolonged duration, spatial variations, and involvement of numerous sectors. Therefore, AI-assisted digital transformation and intelligent upgrades will be pivotal in ensuring the smooth evolution of DHN.

2.2 AI-assisted lifecycles of DHN amid low-carbon evolution

The transformation of DHN is fundamentally a temporal evolution, underpinning reconfiguration across multiple spatial scales and coordination among various stakeholders. Consequently, this review focuses on the evolution of multiple time scales, delving into the strategic application of AI across the entire lifecycle of DHN evolution. Fig. 3 illustrates the different stages involved in the lifecycle of DHN, encompassing planning and design, construction and renewal, operation and control, and maintenance and fault diagnosis.

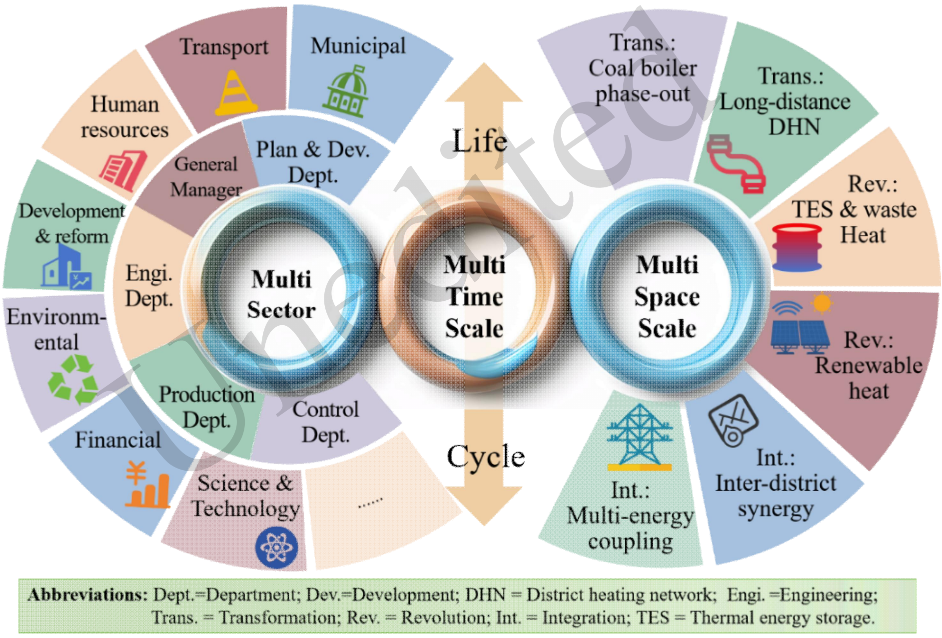

Fig. 2 The three core characteristics for the transformation of 5GDHN

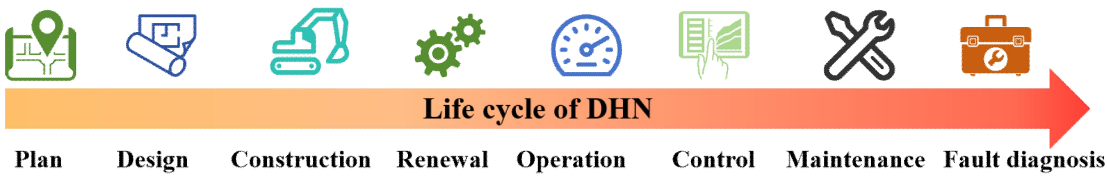

Fig. 3 Lifecycle of a DHN

AI is a critical driver of the ongoing evolution within DHN. Its application provides robust support for intelligent heating management, permeating every stage of the DHN lifecycle. Specifically, as illustrated in Fig. 4, AI can optimize planning and design methodologies, enhance the efficiency of construction schemes, bolster operational strategies, refine the precision of heating control mechanisms, and improve fault diagnosis protocols. In the planning and design phase, AI can enhance design quality and efficiency by constructing surrogate models and leveraging intelligent algorithms.

In the construction and renewal stage, AI can leverage NLP techniques to analyze technical documents and computer vision techniques to analyze on-site images, providing real-time support for risk management and engineering progress tracking. In the operational and control stage, AI can empower load forecasting, the establishment of DHN models, and operational regulation, thereby enabling precise control of the DHN system. In the maintenance and fault diagnosis stage, AI can intelligently diagnose and locate leak positions and types, thus improving the operational safety. These applications not only enhance the efficiency of heating management but also improve the resilience of DHN, enabling them to better handle the intermittent nature of renewable heat sources and fluctuations in both supply and demand (Zhou et al., 2024).

The following sections will review the specific strategies and methods for integrating AI at each lifecycle stage of DHN evolution.

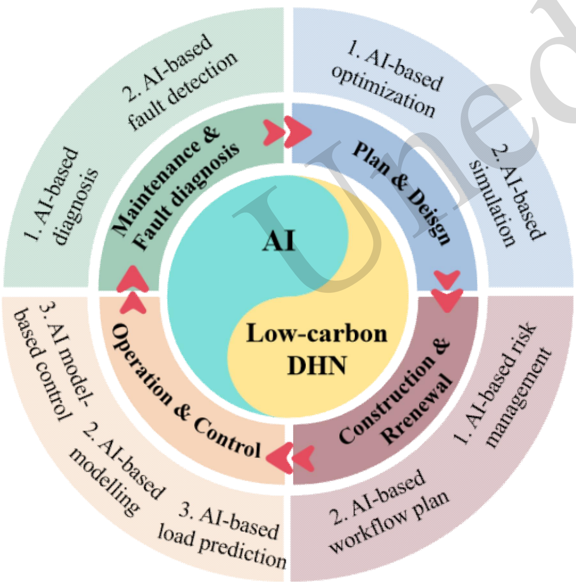

Fig. 4 Overview of AI in the lifecycle of DHN

3 Artificial intelligence applications across the DHN lifecycle

The integration of AI technologies throughout the DHN lifecycle represents a fundamental shift from traditional empirical methods towards a data-driven paradigm that offers measurable gains in efficiency, reliability, and sustainability. To provide a high-level benchmark before delving into the specific technical pathways of each stage, Table 3 synthesizes key quantitative data from state-of-the-art studies. This summary highlights the transformative impact of AI—ranging from order-of-magnitude improvements in design efficiency, to significant reductions in operational costs and fault lead times. As such, this points to its importance in the transition to next-generation heating systems.

Table 3 Key performance indicators and quantitative benefits of AI integration across DHN lifecycle stages

Lifecycle	Improvement Area	Key Quantitative Data	Reference
Planning & Design	Computational Efficiency	99.5% improvement (variables 246 -> 63)	Xu et al. (2024)
	Simulation Speed	0.77 s optimization time	Lambert and Spliethoff (2024)
	Heat loss accuracy	0.65% average error	Chen et al. (2022)
	Low-temperature efficiency	30% reduction in heat loss	Terhan (2022)
Construction	Project timeline	50% faster completion	Sholeh et al. (2020)
	Construction cost	52.36% cost reduction	Sholeh et al. (2020)
	Safety monitoring	88% accuracy (YOLOv8)	Woźniak et al. (2025)
	Progress tracking	30% better reporting accuracy	Cademix (2023)
Operation & Control	Load forecasting	59.4% error reduction	Boutarene (2025)
	Pump performance; energy savings	25% increase in COP; 13% average saving	Ise (2024)
	Forecasting error	MAPE reduced from 21.2% to 8.6%	Boutarene (2025)
	Electricity bill	10.6% power cost savings	Almatared et al. (2025)
Maintenance	Leakage detection	85.85% to 97.5% accuracy	Yang et al. (2024)
	Early warning	3.9 days average lead time	Roelofs et al. (2025)
	Downtime	47.6% fewer unplanned outages	Marhy (2023)
	Asset life	20% lifespan extension	Marhy (2023)

3.1 Planning and design

The planning and design phase of DHN is a complex, multi-stage optimization problem, which is fundamentally concerned with the configuration of pipelines, heat substations, and related components. As shown in Fig. 5, a widely adopted framework for this phase divides the planning process into four hierarchical levels (Schmidt and Stange, 2021): Level 0 uses geographic information systems (GIS) to collect data on heat loads and potential heat sources; Level 1 ensures hydraulic balance and determines key operating parameters; Level 2 optimizes the network topology and pipeline routing; and Level 3 solves the high-dimensional optimization problem of pipe diameter selection, which directly determines capital investment. Another critical optimization tier, situated between Levels 2 and 3, involves the synergistic selection of insulation materials and thicknesses to balance heat losses with material costs; this represents a classic trade-off between operational and capital expenditures (Chen et al., 2022).

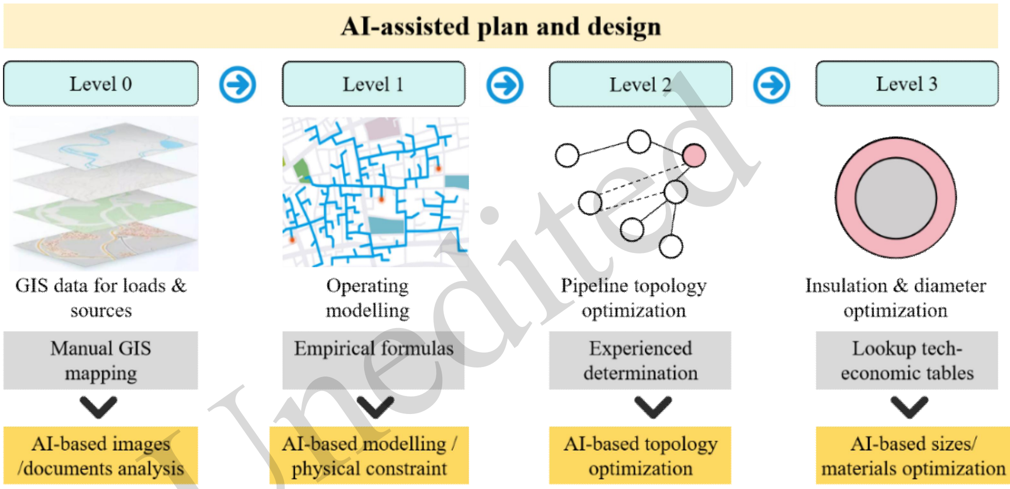

Fig. 5 Optimization levels in AI-assisted planning and design

To overcome these limitations, AI, particularly evolutionary optimization algorithms (EOAs), has emerged as an alternative paradigm. EOAs – including methods such as simulated annealing (SA), ant colony optimization (ACO), and particle swarm optimization (PSO) – are well-suited to the complex design landscape of DHN. Their primary advantages lie in their gradient-free nature and their ability to handle non-linear, non-convex, and non-differentiable objective functions without sensitivity to initial conditions (Sarbu et al., 2019). This makes them highly effective for optimizing diverse facets of DHN design, such as pipe sizing, substation siting, and network topology (Su et al., 2022).

In a large-scale network case study in Xi'an, IGA reduced the number of design variables from 246 to 63, and the number of iteration steps from over 6,000 to less than 60. This resulted in a 99.5% improvement in computational efficiency and a reconstruction profit of 25.4 million CNY (Xu et al., 2024). The main drawback of EOAs, however, is their potentially high computational cost for large-scale problems.

Complementing this direct optimization approach, artificial neural networks (ANN) offer a distinct, data-driven paradigm that functions primarily as a surrogate model or an accelerator within the design workflow. The data sources for these networks can be derived from simulation software such as *TRNSYS* (Abokersh et al., 2020), or calculated using mathematical formulas, such as those from lifecycle design analysis and heat-loss mechanistic models (Kayfeci et al., 2014; Chen et al., 2022). Related research has explored the application of ANNs to precisely determine the optimal insulation thickness. For instance, Chen et al. (2022) developed a data-driven model employing an ANN to reconcile discrepancies between measured and theoretical heat-loss values in pipeline networks, and to augment available datasets. This ANN-based approach reduced the average error in predicting the actual heat loss to 0.65% (Chen et al., 2022). The

ANN model was able to map various input parameters – including pipe diameter, the thickness and material of each insulation layer, flow rate, pipe temperature, pipe length, and pressure rating – to corresponding heat loss values. Moreover, optimizing temperature levels (e.g., from 80/40°C to 60/30°C) can reduce the network heat loss by up to 30% (Terhan, 2022).

Subsequently, a nonlinear programming algorithm was executed using *MATLAB* to further optimize the optimal thickness configuration for each insulation layer. This study by Kayfeci et al. (2014) focused on employing ANNs to predict the optimal insulation thickness and its associated lifecycle costs (LCC). By first establishing optimal values through traditional LCC analysis, and then training an ANN to learn this parametric relationship, a rapid prediction tool that could generalize to various operating conditions was obtained; as such, the need for repetitive, computationally intensive calculations was dramatically reduced. In both cases, the ANN does not replace the optimization algorithm but rather augments it by providing a fast and accurate approximation of the objective function or constraints, thereby streamlining the design process.

In conclusion, while traditional optimization methods remain relevant for specific, simplified scenarios, AI-based techniques – particularly EOAs – have emerged as the dominant paradigm for tackling the intricate design challenges of next-generation DHN. However, their widespread adoption is still contingent on overcoming the hurdle of high computational intensity, which remains a primary focus of ongoing research and development.

3.2 Construction and renewal

3.2.1 Construction risk assessment

Large-scale DHN exhibit three key characteristics during the construction phase: long project durations, extensive distances covered, and high cost and risk exposure. These factors make DHN construction projects particularly vulnerable to delays, safety incidents, and budget overruns; large-scale DHN construction is particularly susceptible to budget overruns. AI technologies have proven effective in mitigating such challenges within broader construction projects (Kazeem et al., 2023), and their potential to improve risk management in DHN projects is being increasingly recognized. Case studies on market-based AI frameworks have reported annual cost savings on the order of hundreds of thousands of US dollars, along with relative market efficiency improvements of approximately 28% (Dmytro et al., 2024).

(1) Pre-construction risk assessment

As illustrated in Fig. 6, before construction, AI techniques can be employed to systematically assess contract documents, drawing errors, and other potential issues. Additionally, techniques like NLP can automate the analysis of construction contracts, enabling the detection of critical issues such as missing clauses and ambiguous terms, with reported F-measure values ranging from 70.0% to 88.4%, and recall rates from 84.6% and 99.3% across different contract analysis tasks (Dikmen et al., 2025a). Additionally, AI algorithms have the ability to analyze drawing errors and discrepancies, enabling early identification of project vulnerabilities such as inaccurate man-hour estimates or resource allocation issues (Choi et al., 2021).

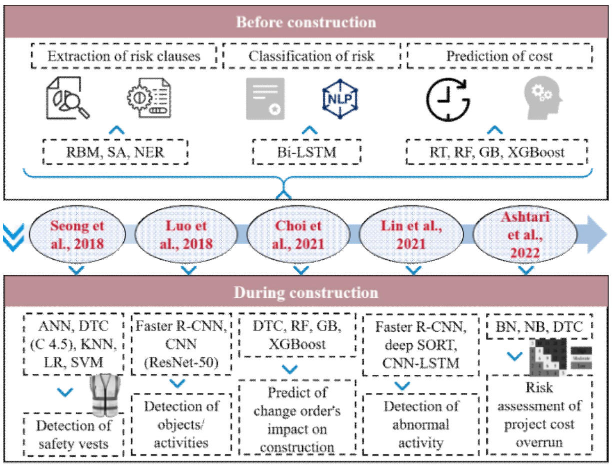

Fig. 6 AI techniques applied to construction risk assessment

(2) Risk management during construction

During the construction phase itself, AI facilitates comprehensive, real-time risk management, such as handling scope changes and controlling cost overruns (Ashtari et al., 2022). In terms of site safety, computer vision algorithms (e.g., YOLOv8) for monitoring hardhat compliance achieved 0.88 accuracy and 0.93 precision (Woźniak et al., 2025). AI systems have also reduced construction monitoring costs by 10% while increasing progress reporting accuracy by 30% (Cademix, 2023). Furthermore, computer vision-based AI technologies can be utilized to bolster on-site safety measures. Specifically, during DHN pipeline construction, the simple online and real-time tracking (SORT) method enables real-time monitoring of the worksite environment with a multiple object tracking accuracy of 82%. This includes terrain analysis and identification of potential hazards via drone inspections, as well as dynamic prediction and adjustment of construction progress (Lin et al., 2021).

Methods like expert system models are commonly used AI techniques in construction management, and enable new problems to be solved by leveraging existing experience; examples include rule-based matching (RBM) and case-based reasoning (CBR) (Yau and Yang, 1998). Nevertheless, expert system models still face challenges in contemporary construction management, including imperfections in their systems, the lack of real-time data streams, and deficiencies in case similarity definitions and retrieval mechanisms. NLP algorithms have also been applied to automated risk analysis of construction contracts, demonstrating promising baseline performance in tasks such as named entity recognition (NER) and semantic analysis (SA).

Within the realm of ML, supervised learning is widely employed for training models and evaluating their applications in risk management and construction safety supervision; commonly used models include the decision tree classifier (DTC), regression tree (RT), random forest (RF), gradient boosting (GB), XGBoost, Bayesian network (BN), Naive Bayes (NB), K-nearest neighbors (KNN), linear regression (LR), and support vector machine (SVM). Given that the performance of different ML algorithms varies across tasks and even on the same task using other datasets (as encapsulated by the no free lunch theorem) (Xu and Saleh, 2021), nearly all studies conduct comparative analyses across multiple ML algorithms, examining the impact of various hyperparameters on the model results and generalization capabilities. However, ML models often require manual feature engineering, for example by exploring different color spaces, making them less practical for direct deployment on construction sites (Seong et al., 2018).

Deep learning methods have gained traction in safety monitoring due to their capabilities in adaptive feature extraction and generalization, leading to notable applications such as bidirectional long-short term memory (Bi-LSTM), fast region-based convolutional networks (F-RCNNs), and simple online and real-time tracking with a deep association metric (Fang et al., 2018). However, since detection based solely on individual image frames fails to capture sequential actions such as the cyclical movements of an excavator, the integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) has become a promising trend (Luo et al., 2018). When processed through hybrid CNN-RNN architectures, multimodal data streams enable temporal pattern recognition of precursor signatures corresponding to structural failures or operational hazards.

3.2.2 Construction workflow planning

The extended construction lifecycle characteristic of large-scale DHN necessitates the application of AI technologies to support the following critical aspects: 1) Construction progress management, and 2) Quality control and construction process management (Baduge et al., 2022), as shown in Fig. 7. Our subsequent discussion will focus on these two points. It should be noted that the following analysis draws insights from the broader architecture-engineering-construction (AEC) industry, as DHN construction is an integral component of urban infrastructure development and falls under the category of municipal public works(Hanafy, 2025).

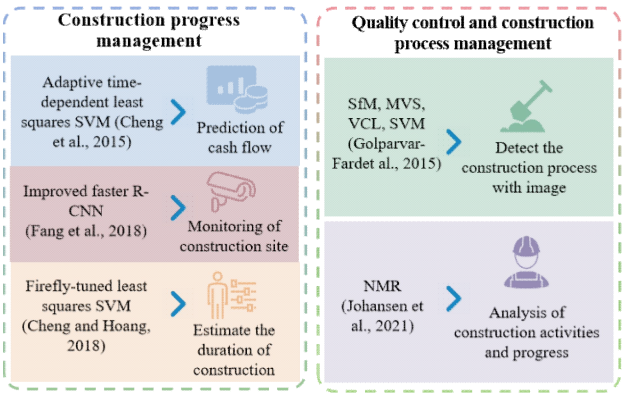

Fig. 7 AI techniques applied to construction workflow

planning

Construction progress management primarily aims to address cash flow and cost control throughout the construction lifecycle, as well as to optimally allocate labor and resources over the project duration. For example, an average deviation in construction cash flow predictions as low as 1.8% was achieved using a time-dependent least squares SVM (Cheng et al., 2015).

Quality control and construction process management, on the other hand, focuses on implementing comprehensive monitoring throughout the construction lifecycle; it encompasses both quality and progress oversight. For instance, computer vision techniques such as structure-from-motion, multi-view stereo (MVS), and voxel coloring and labeling (VCL) are often used to reconstruct three-dimensional models from unordered two-dimensional photographs (Golparvar-Fard et al., 2015). This approach effectively addresses occlusion and partial visibility issues, enabling AI systems to analyze the state of construction elements from multiple perspectives and manage complex 3D construction scenarios. To quantify this, automated progress detection accuracies of 82.89% ~ 91.05% have been achieved for real construction datasets, as-built and as-planned model registration errors were within 0.20–0.73 mm, and the progress monitoring efficiency increased by more than 80% compared with manual methods (Golparvar-Fard et al., 2015). Non-monotonic reasoning (NMR), when integrated with field data and a construction knowledge base, facilitates logical inference within answer set programming (Johansen et al., 2021). By applying predefined rules, it can assess worker states and basic operational behaviors, thereby improving construction efficiency and progress.

By applying AI to track timelines, allocate resources, and monitor construction quality in real time, projects can be completed more efficiently and with fewer risks. The integration of advanced computer vision and reasoning techniques further enhances the ability to manage complex construction processes, improving overall outcomes.

3.3 Operation and control

3.3.1 Load forecasting

Load forecasting is an essential component of operational control in DHN, and represents one of the primary application domains for AI technologies (Mbiydzenyuy et al., 2021). A mainstream development trend involves integrating forecasts of individual building thermal loads into regional thermal loads (Sakkas and Abang, 2022). Two methodologies are primarily employed: physics-based engineering methods and data-driven approaches (Jiang et al., 2022). This review focuses predominantly on data-driven methods, particularly those leveraging AI.

Previous reviews in this field have noted that ML methods remain the dominant technology, with hybrid approaches combining techniques such as ANN and SVM attracting increasing research interest (Xue et al., 2019; Mbiydzenyuy et al., 2021). ML techniques demonstrate significantly higher accuracy than traditional statistical regression methods (Geysen et al., 2018; Jiang et al., 2022). As an example, in heat load forecasting, a hybrid denoising autoencoder-LSTM model reduced the MAPE from 21.2% to 8.6% in high-noise IoT environments—representing a performance gain of 59.4% (Boutarene, 2025). Moreover, in Denmark, large operators achieved 15% to 30% accuracy improvements in forecasting (Madsen, 2023). However, there is no conclusive evidence identifying a universally superior ML model for specific problem domains. Furthermore, data quality and scale are arguably more critical factors for enhancing the predictive accuracy (Zdravkovic et al., 2022).

As depicted in Fig. 8, a variety of models are widely utilized in load and thermal load forecasting studies (Idowu et al., 2016), such as multiple linear regression (MLR), linear regression (LR), extra tree (ET), support vector regression (SVR), deep neural networks (DNNs), ridge regression (RR), AutoRegressive with eXogenous input (ARX) models, fuzzy logic (FL), partially linear models (PLMs), graph neural networks (GNNs) (Wang et al., 2023b), and ensemble methods (Johansson et al., 2017; Shakeel et al., 2023). Among these, traditional ML models – particularly SVMs – are prevalent.

In the realm of AI techniques, ANNs are sometimes regarded as the optimal model (Kurek et al., 2021), while at other times, they are considered inferior to models such as SVMs (Mbiydzenyuy et al., 2021). By integrating real-case data into system training, ANNs can account for social parameters, thereby enhancing the adaptability and accuracy of load forecasting. However, a primary drawback of this method is the potential for overfitting and the need for substantial training data. Therefore, the essence of achieving superior prediction results lies in the alignment between the model, the data quality, the data quantity, and the task at hand.

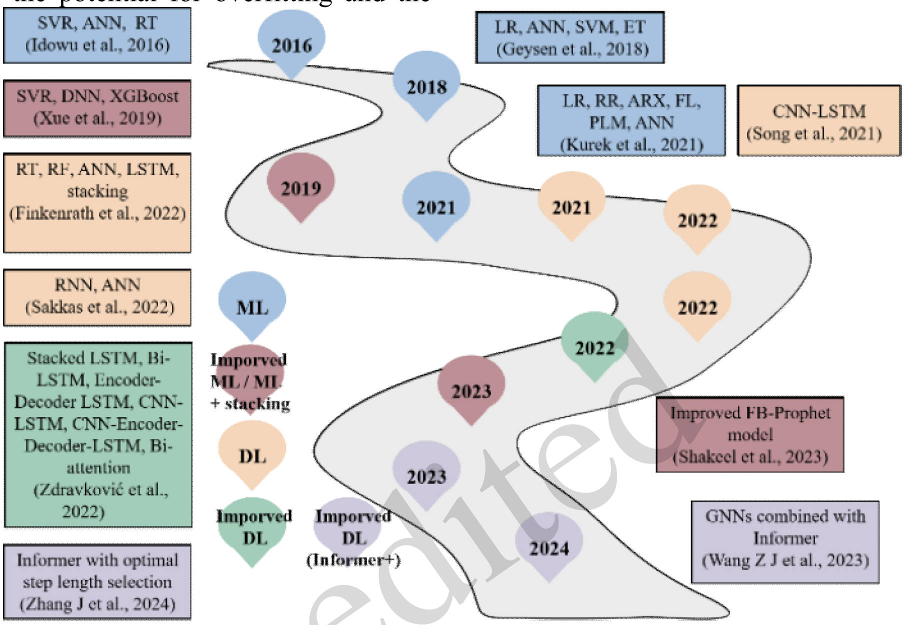

Fig. 8 AI techniques applied to thermal load prediction

At the same time, DL models are increasingly being applied for forecasting (Song et al., 2021). Based on Transformer architectures, Informers use improved sparse self-attention mechanisms. This significantly enhances the efficiency and accuracy of long-sequence time series forecasting, making it well-suited for complex load prediction tasks (Gong et al., 2022; Wang et al., 2023b). While ML and DL methods offer substantial advantages over traditional forecasting techniques, their success depends heavily on alignment between the type of model, the data quality, and the specific characteristics of the forecasting task. Future research should continue to explore hybrid models and further refine data-driven techniques to improve the reliability and precision of load forecasting for DHN.

3.3.2 Hydraulic and thermal modeling

The development of a digital twins for DHN can be achieved by establishing hydraulic and thermal models, which are crucial for optimized operation and control. Modeling of heating networks typically employs either physical modeling methods or data-driven methods (Bella et al., 2021). The former involves individually designing each component and expressing its flow and pressure loss using sets of equations. Meanwhile, the latter utilizes methods such as the overall network's transfer functions or ANNs. Hydraulic and thermal models are traditionally developed based on graph theory, conceptualizing the heating pipeline network as a graph structure and utilizing incidence matrices and loop matrices based on Kirchhoff's laws to comprehensively and uniquely describe its topology.

Hydraulic models primarily rely on the continuity equation for flow and the pressure balance equation to analyze flow distribution and pressure losses within the network. Conversely, thermal models employ heat balance equations to evaluate the system's heat demand, heat losses, and heat exchange processes at the consumer end. These models holistically consider pipe geometric characteristics, fluid physical properties, and operating conditions, providing a theoretical foundation for the design, optimization, and operation of heating networks (Sarbu et al., 2019). Commercial software packages, such as *TERMIS* (Saarinen and Boman, 2012) and *Modelica* (Arce et al., 2018), serve as powerful tools for the design, optimization, and operational management of heating networks. However, this review mainly focuses on the application of AI techniques in DHN modeling, specifically highlighting the integration of AI with data-driven DHN modeling approaches as illustrated in Fig. 9.

The core idea behind using AI techniques as alternatives to physical models is to develop methods that learn and replicate the physical dynamic behavior of heat substations or consumer nodes within a DHN, while also incorporating physical model insights into the data-driven framework. The aforementioned AI techniques possess distinct advantages in the context of heating network modeling, but also exhibit certain limitations. Future research directions in heating network modeling might concentrate on the following aspects: 1) Combining the strengths of linear and non-linear models to enhance the applicability and accuracy of the methods; 2) Further optimizing the incorporation of physical constraints to improve model robustness and interpretability (Lu et al., 2024); 3) Reducing the computational cost of complex models through algorithmic optimization and hardware acceleration (Rodrigue et al., 2024). Therefore, a combination of data and physical information is needed in AI-based modelling of DHN. The physical guided STGCN model achieved an average error of 0.5 K and 0.002 bar in prediction of DHN, and its computational time was 99% less than traditional dynamic calculation methods (Boussaid et al., 2024). Additionally, by adding physical information, the lower bound of the predicted R2 could be increased by 74.6% with the PI-GRU method (de Giuli et al., 2024).

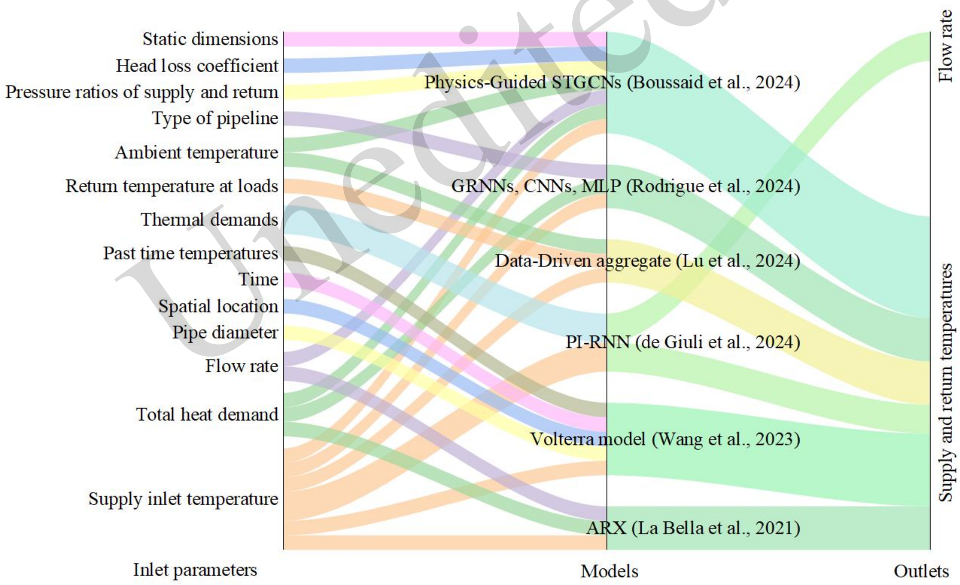

Fig. 9 AI techniques applied to hydraulic and thermal modelling

3.3.3 Optimal operational control

Recent studies have also explored physics-informed neural networks (PINNs) to support both DHN modelling and predictive control (De Giuli et al., 2024). Operational control of DHN (Boussaid et al., 2024) aims to optimize the heating system's operational efficiency and reduce energy waste through intelligent scheduling and real-time regulation. Traditional control methods – such as rule-based control and PID control (Ntakolia et al., 2022) – are increasingly struggling to meet economic regulation demands (Lee et al., 2020) for DHN supply-demand matching under the trends of high renewable heat integration and convergence of multi-type energy networks (Buffa et al., 2021). Therefore, the development of AI-based operational control strategies and technologies for DHN is becoming increasingly vital.

As Buffa et al. (2021) suggests, advanced control technologies can be primarily categorized into model predictive control (MPC), linear programming, mixed integer programming (MIP), mixed integer linear programming (MILP), and multi-agent systems (MAS) (Wei et al., 2024). In a district heating network case study from Verona, MPC achieved a reduction of about 12.5% in operational costs during a representative mid-season week, and 5.8% in a winter week, as compared to conventional control (Quaggiotto et al., 2021). When the flexibility was increased by adding centralized heat storage, the cost reductions increased to 20% and 6.3%, respectively. Among these, MAS employs various control schemes to manage different types of agents within DHN or buildings, addressing interdependencies among control variables through agent coordination (Wang et al., 2023a). The aforementioned control methods can be integrated with various AI techniques. In MPC, predictive accuracy is critical, and AI-optimized MPC frameworks, often using hybrid surrogate models, enable real-time multi-boiler control, reducing energy costs by up to 29% (Boussaid et al., 2026) and emissions by up to 23.3 tCO_2 (Mugnini et al., 2022). Notably, traditional physical models can struggle to describe complex dynamic systems. In contrast, machine learning (Johansson et al., 2017) and DL models (Xue et al., 2020) can leverage historical data to learn a system's dynamic characteristics, thereby enhancing predictive and control accuracy. Furthermore, in dynamically changing environments, system parameters will vary. Adaptive control techniques combined with AI enable real-time adjustment of MPC parameters to adapt to different operating conditions (Lauenburg and Wollerstrand, 2014). In the context of MILP, optimization algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) can be employed to reduce the solution time, addressing the demands of high-dimensional nonlinear optimization and regulation (Urbanucci et al., 2019).

However, as shown in Fig. 10, RL techniques are gradually emerging as a research hotspot (Solinas et al., 2021; Gong et al., 2024). Unlike MPC, which integrates AI-based predictive models as the basis for its control actions, RL often uses reduced-order or surrogate models (Pinto et al., 2021) to predict states or reward functions (Zhang et al., 2019). Despite the significant potential demonstrated by RL, several challenges persist. First of all, there are often issues with the quantity and quality of the training data. Although there exist simulation software packages (e.g., *EnergyPlus*, *TRNSYS*) or specific environments (e.g., *CityLearn*) for training, it is challenging to ensure tight consistency between simulation and reality (the sim-to-real gap) before deployment in real systems. Secondly, the training process is typically complex and computationally intensive. RL training can be unstable, requiring meticulous hyperparameter tuning and substantial computational resources, which may pose obstacles for practical applications. Thirdly, RL policies generally offer limited interpretability, which can be a disadvantage in energy systems where strict safety regulations must be met, or detailed fault diagnoses are required.

In summary, AI-based control strategies – such as MPC, MILP, MAS, and RL – are key to improving DHN operational efficiency under complex and dynamic conditions (Finkenrath et al., 2022). While RL shows great promise, challenges such as data requirements, computational demands, and limited interpretability remain. Addressing these issues is crucial for deployment in real-world systems.

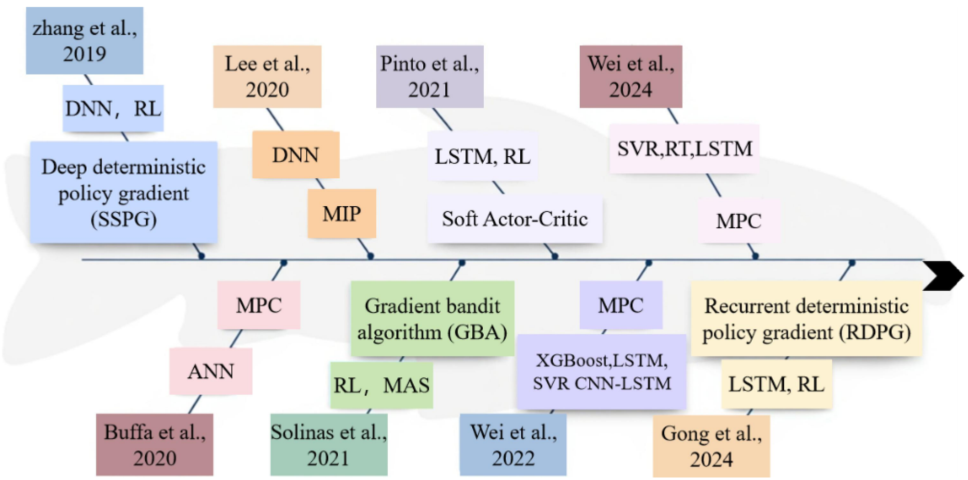

Fig. 10 AI techniques applied to operational control research

3.4 Maintenance and fault diagnosis

Beyond daily operation and control, efficient operation necessitates maintenance and fault diagnoses for DHN. As DHN continue to expand and the integration of multiple networks deepens, manual maintenance and monitoring techniques are becoming increasingly challenging. Timely fault localization and quantitative assessments within DHN have become more difficult, posing obstacles to large-scale operation. Xue et al. (2020) demonstrated that XGBoost-based models for leak identification achieved an average accuracy of 85.85%; more advanced hybrid models have reached 97.5% accuracy levels in leakage localization (Yang et al., 2024). Therefore, the adoption of AI technologies is particularly promising.

At this stage, routine maintenance of DHN primarily requires technologies for monitoring and metering (Palasz and Przysowa, 2019), while fault management mainly relies on fault detection and diagnosis (FDD) (Losi et al., 2024). Monitoring and metering primarily aim to continuously monitor changes in temperature, pressure, and flow within a DHN to promptly identify anomalies, including those related to sensors themselves and within the DHN system (Li et al., 2020). FDD seeks to assist operation and maintenance personnel in quickly formulating repair plans by promptly identifying fault types (such as pipeline leaks, heat loss, pressure loss) and locating their positions, both before and during a fault event (Xi et al., 2024). AI models have been shown to detect 60% of faults before customers report them, with an average lead time of 3.9 days (Roelofs et al., 2025).

Maintenance and fault diagnosis for DHN can be achieved using both physics-based and data-driven methods (Manservigi et al., 2022). Physics-based methods require the construction of numerous models, often via digital twins (Bahlawan et al., 2022), and their accuracy can be unreliable in actual operational scenarios because DHN model parameters may deviate significantly over time. In contrast, data-driven methods – particularly those incorporating AI technologies – can rapidly and accurately implement detection through pattern analysis of monitoring data (Shen et al., 2021).

As can be observed from Table 4, research on pipeline leakage detection dominates studies that concern fault detection and metering. However, there is a relative lack of research focusing on the operation, maintenance, fault diagnosis, and monitoring of other DHN systems, such as heat substations and pumping stations. Furthermore, few studies explicitly discuss data related to the speed and real-time performance of detection. This aspect partially depends on the output capability and speed of the specific AI model, and partially on the frequency and interval of the collected data. Thus, it is essential to understand the response speed and time-consumption aspects of AI technologies applied to pipeline leakage and fault detection, differentiating it from manual operation and maintenance approaches.

Regarding AI techniques, most studies combine simulations/modeling with neural networks to extract fault-related information, and use it to train AI systems for timely fault detection and localization. While it is effective for known faults, this approach cannot handle fault information that is not present in the simulations. Consequently, fault diagnoses based on data generated through experiments or simulations and combined with AI techniques may lack practical utility (Bode et al., 2020; Buffa et al., 2021). Simultaneously, anomaly detection methods exhibit significant variations depending on the specific application, meaning their evaluation also differs based on their inherent characteristics and the nature of the datasets used (Mbiydzenyuy et al., 2021).

Table 4 AI techniques applied to fault detection and metering

Detection tasks	AI technologies	Ref.
Failures of components	CNN	Li et al. (2020)
Failures of components	SVM, ANN, Bagging DTC	Palasz and Przysowa (2019)
Pipeline leakage detection and localization	XGBoost (CARTs-based)	Xue et al. (2020)
Pipeline leakage detection and localization	Contextual bandit	Shen et al. (2021)
Pipeline leakage detection and localization	ANN	Liu et al. (2023)
Pipeline leakage detection and localization	Cuckoo search algorithm and clustering	Xi et al. (2024)
Pipeline pressure and heat loss	Nonlinear autoregressive network with exogenous inputs neural network	Losi et al. (2024)

To address these challenges, transfer learning methods could be explored, leveraging real-world fault detection data to enhance the quality of the training datasets (Liu et al., 2023). Concurrently, the development of RL-based fault detection methods warrants further investigation. Given that DHN systems operate under dynamic conditions with numerous interacting factors, digital twin models often fail to detect sudden faults. However, RL's ability for sequential decision-making and predictive foresight – utilizing historical data to anticipate future states – offers a promising approach for proactive fault detection and early warning systems.

4 Opportunities and challenges for integrating AI into the DHN lifecycle

Based on the lifecycle stages of DHN discussed above, the opportunities and challenges of AI can be summarized as shown in Fig. 11.

4.1 Dynamic planning and multi-period design

DHN serve large communities or cities and are inherently dynamic, especially during their evolution over time. Factors such as population growth, changes in land use, increasing building density, and adjustments in functional zoning all influence the heat load distribution. Consequently, static planning models may struggle to keep pace with urban evolution, necessitating continuous updates. DHN planning and design requires constant updates to align with the city's development and evolution of the DHN. Therefore, in addition to the integration of cleaned GIS and actual operational data (Wang et al., 2021b), AI-enhanced modelling should be improved to create high-fidelity digital twins and enhance the accuracy and reliability of planning outcomes.

Due to the development and scaling-up of urban clean energy, the design of DHN cannot be completed in a single step. As heat sources, thermal loads, and network topologies evolve throughout the planning process, it becomes necessary to revisit and redesign the system at multiple critical nodes. AI-enabled retrofit planning and control strategies have yielded 17–77% CO_2 emission reductions in case studies; moreover, TES optimization has lowered emissions by 17.33% (Hassan et al., 2024; Seraj et al., 2025). This necessitates the development of AI agents capable of automatically executing multi-period rolling design optimization decisions for the DHN, specifically through analytical judgments and decision making, thereby ensuring that the design outcomes continuously meet operational demands.

At the same time, DHN are evolving towards greater integration with thermal storage (Mehraj et al., 2024) and renewable heat sources, such as geothermal, industrial waste heat, solar thermal, and biomass resources (Jiang et al., 2022). Beyond merely optimizing the design parameters of DHN, it is essential to develop AI-based models of renewable energy systems and integrate them into the design process, so as to enable coordinated optimization.

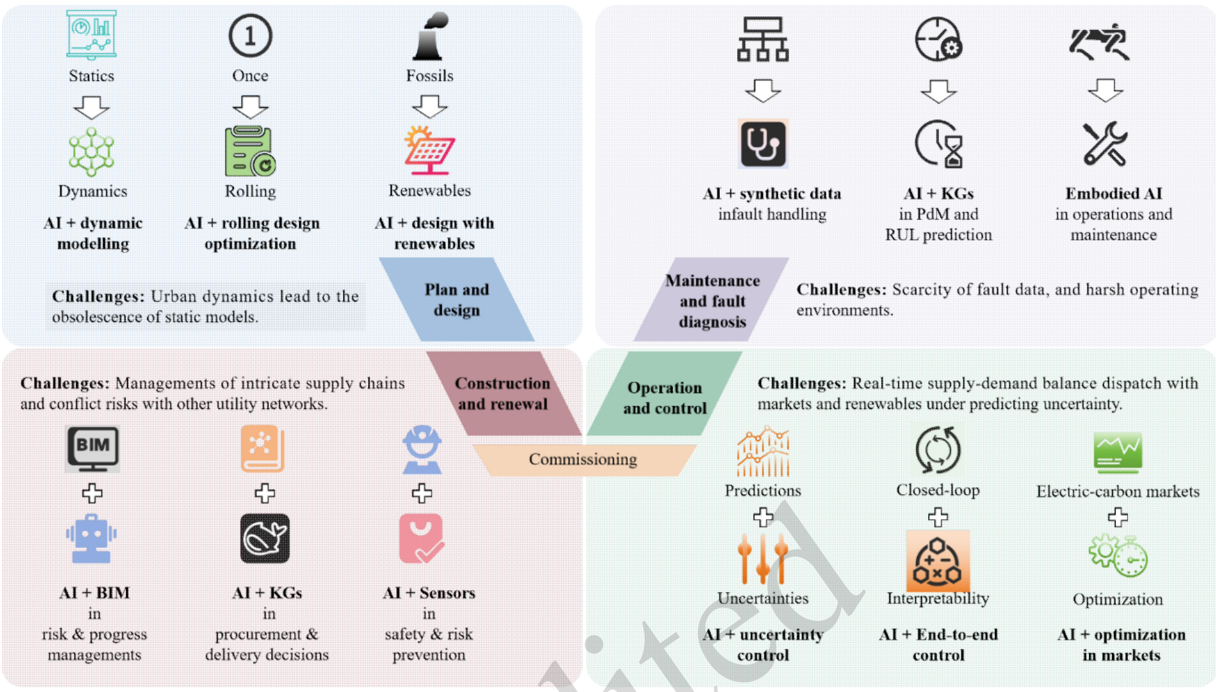

Fig. 11 Summary of the opportunities and challenges for AI within the DHN lifecycle

4.2 Enhancing BIM integration, supply chain efficiency, and safety systems

DHN projects inherently involve a full lifecycle: pre-construction, construction, and post-construction phases (Choi et al., 2021). An automated platform consolidates risk management and decision-making at each stage across the entire lifecycle, but AI integration still requires improvements in key areas. On the one hand, enhanced AI integration with building information modeling (BIM) is essential to avoid utility conflicts with other networks in large DHN projects, such as gas and water networks – this has been proven to cut construction time by 50% and reduce total costs by 52.36% (Sholeh et al., 2020). On the other hand, resource and supply chain management is crucial for efficiency improvement and waste reduction in construction (Abioye et al., 2021). An AI-driven supply chain platform can leverage knowledge graphs (KGs) and large language models (LLMs) to dynamically analyze market and supplier data, thus optimizing procurement decisions for construction (Mishra et al., 2024). AI-assisted forecasting of the supply-demand relationship for construction materials should also be established, proactively initiating replenishment requests and planning optimal delivery routes.

Additionally, AI enables the establishment of an intelligent safety and risk prevention system for construction. In the context of contract risks, traditional expert systems or NLP models demonstrate limited effectiveness when faced with complex projects (Dikmen et al., 2025b). But integrating fine-tuned transformer models such as BERT can enhance generalization capabilities. For cash flow and safety risks, a collaborative and comprehensive framework between intelligent decision-making systems and smart sensing devices should be established, such as the "digital skin" concept proposed by Edirisinghe (Edirisinghe, 2019) using smart wearables. Such a framework is essential to meet the demands for comprehensive protection, real-time responsiveness, and early warning in the complex construction of DHN.

4.3 Optimization and control of operations under uncertainties

Thermal load forecasting is critical for the optimization of district heating networks (DHN), as it directly determines the accuracy of supply–demand matching. However, uncertainties on both the supply and demand sides pose significant challenges to reliable prediction. AI-based uncertainty quantification techniques enable the explicit decomposition of predictive uncertainty, accordingly improving model robustness and decision reliability (Abdar et al., 2021). Recent studies further demonstrate that physics-informed transfer learning can significantly enhance extrapolation performance under unmeasured operating conditions, reducing aleatoric, epistemic, and total uncertainties by 73.4%, 70.4%, and 72.2%, respectively, while maintaining prediction errors within ASHRAE-recommended limits (Kim et al., 2025). In addition, integrating historical and real-time IoT data is essential for improving model adaptability under dynamic operating conditions.

Building upon uncertainty-aware predictive models, advanced optimization and control strategies have been shown to deliver measurable system-level benefits. Published studies have reported reductions in peak demand and operational variability, while AI-optimized thermal energy storage sizing and operation can reduce investment costs by 4–7% (Jebamalai et al., 2020), and operational costs by up to 18% (Dominik et al., 2022); these results provide quantitative benchmarks for evaluating the performance of uncertainty-aware control strategies. Future research should focus on integrating AI frameworks with probabilistic forecasting, uncertainty propagation, and optimization-based control to facilitate more robust DHN operation and management.

Moreover, an end-to-end control loop leveraging AI should be established. To address practical demands such as real-time control, optimized scheduling, supply-demand balance, cost-benefit analysis, and data acquisition, future research should be dedicated to constructing AI surrogate models using mechanistic models and data, as well as integrating them into advanced control strategies such as MPC and RL. Furthermore, it may be worthwhile to leverage LLMs to generate explanatory documentation, thereby enhancing the interpretability of AI control strategies and increasing the credibility of decision-making.

The integration of electricity markets and carbon markets is also crucial for developing efficient, low-carbon DHN. In electricity markets, by forecasting thermal loads, electrical loads, and market trends, AI can enable DHN operators to formulate heating and power generation strategies, and also assist distribution network operators (DNOs) in determining transaction decisions. In carbon markets, AI can aid heating enterprises in developing carbon trading and low-carbon strategies by predicting carbon prices and transaction volumes.

Improving fault diagnosis robustness to data issues also remains a challenge, as this is limiting comprehensive application of AI in practical fault identification and handling scenarios. This limitation manifests in several aspects: 1) Data acquisition from real-world operational conditions is challenging due to the high cost of sensor deployment and the scarcity of fault data; 2) AI models typically recognize only a limited number of fault types. To address these challenges, an end-to-end AI-driven fault handling system should be constructed. Such a platform might integrate simulated and real-world data, and leverage techniques such as transfer learning and domain adaptation to enhance generalization ability across diverse DHN systems and operational scenarios.

PdM analyzes current and historical operational conditions to forecast future states, failures, or the remaining useful life of equipment (Upasane et al., 2024); as such, it enables the prevention of pipeline corrosion, heat loss, and equipment malfunctions (Rafati and Shaker, 2024). As an emerging research field, the advancement of PdM relies on the progress of various sensor and metering technologies (Lv and Li, 2021). This transition to PdM has been shown to reduce unplanned downtime by 47.6%, and maintenance-related costs by 40% (Marhy, 2023). In addition to data-driven AI models, the integration of other AI technologies such as NLP and LLMs offers further potential. By parsing unstructured text and constructing knowledge graphs, these technologies facilitate deeper analysis and prediction, consequently reducing reliance on observational data and enhancing model generalization (Sun et al., 2025).

Embodied intelligence, another branch of AI, emphasizes the physical interactions between agents and their environments. In the context of DHN inspection, embodied intelligence is poised to further demonstrate its value. From the air, research should focus on enhancing UAV-based DHN inspection through path optimization (Yan et al., 2019). And on the ground, there is potential for broader adoption of quadruped robots to autonomously read instrument data, detect acoustic signals, and perform other inspection tasks (Zhang et al., 2024c). Inside pipelines, AI-equipped micro-robots are expected to achieve intelligent anomaly diagnosis in a mobile fashion.

5 Summary and outlook

5.1 Summary of the current state

Across the entire lifecycle of DHN—including design, construction, operation, and maintenance—AI has been reported to enhance efficiency, reliability, and cost-effectiveness. Existing studies demonstrate that these benefits are measurable and attainable under specific system configurations and assumptions, with reported examples showcasing substantial reductions in design costs, shortened construction timelines, improved heat pump efficiency, and several days of advance fault warning. These findings indicate that AI offers not merely a conceptual advantage, but a quantitatively robust solution for the transition toward 5GDHN.

However, current research has exhibited fragmentation in focus, leading to several limitations. These include insufficient generalization capability to unforeseen conditions, data silos stemming from incompatible data formats across different phases or departments, and the "black-box" nature of AI, which exacerbates trust barriers and operational risks. This lack of interoperability between different lifecycle stages prevents effective transfer of intelligent outcomes from one phase to another, and also limits the realization of closed-loop optimization across the evolution of DHN. Moreover, although the transformation of DHN relies on continuous feedback loops among design, construction, operation, and maintenance stages, AI outcomes from one phase often fail to transfer effectively to the next—for example, to subsequent design cycles. This hinders the integration of intelligent solutions into a coherent pipeline, and obstructs the path to iterative optimization across the entire DHN lifecycle.

5.2 The digital thread and AI integration

To break down these barriers, it is recommended to adopt a digital thread (DT) paradigm, which provides a unified data stream throughout the whole lifecycle and connects various departments and engineering stages (Wang et al., 2021a); accordingly, it enables seamless information transfer and sharing across lifecycle stages through a persistent semantic backbone that supports interoperability between heterogeneous engineering environments. This capability further supports continuous iterative improvements to the transformation process within a digital twin environment (Zhang et al., 2024a). This capability of providing coherent, real-time data is fundamental to enhancing organizational decision-making. Analysis from industry indicates that adopting a DT framework can enable organizations to accelerate decision cycles by 72%, and improve decision accuracy by 30% (Almatared et al., 2025). Therefore, adopting a digital thread strategy with model-based systems engineering (MBSE) to unify modeling languages and processes has emerged as an imperative choice for breaking down information barriers across the entire DHN lifecycle; it enables effective transfer and closed-loop optimization of intelligent outcomes between different stages (Fu et al., 2021). Fig. 12 illustrates the conceptual architecture of the DHN digital thread paradigm. It depicts a central DT, underpinned by MBSE models, connecting and integrating data and processes across the distinct lifecycle phases of a DHN. In particular, the DT framework is designed to address lifecycle data fragmentation by establishing semantic consistency and structured interoperability across engineering stages.

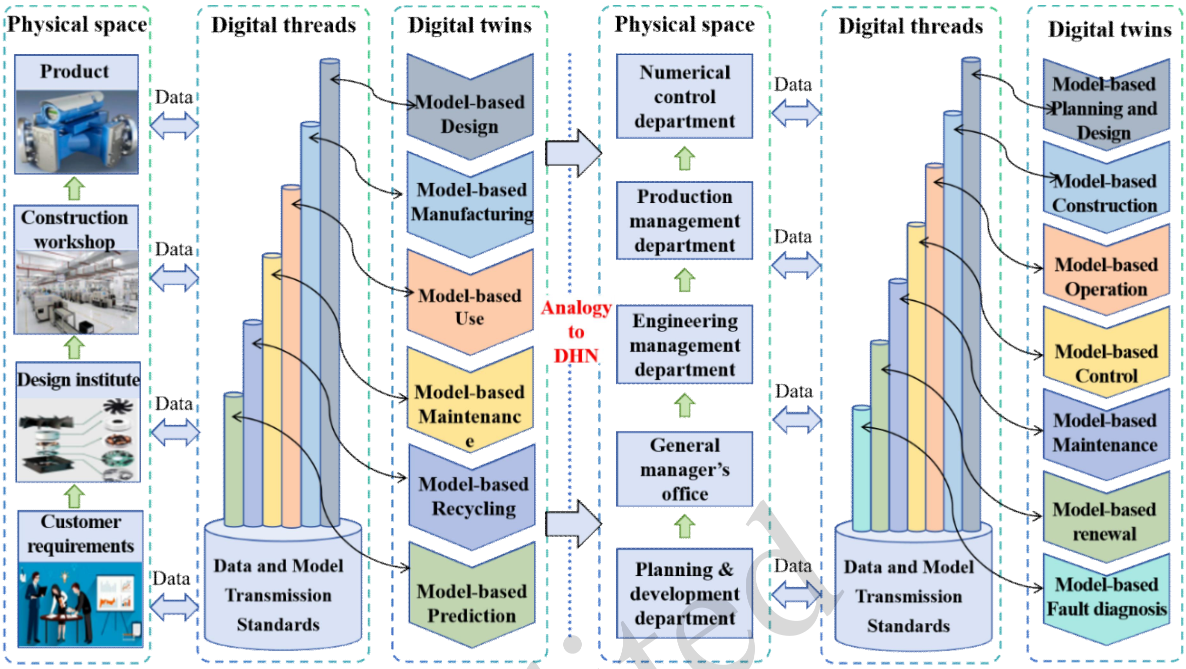

Fig. 12 Conceptual architecture of the DHN digital thread paradigm, showcasing the central thread integrating all lifecycle phases

The DHN DT paradigm emphasizes structured, contextualized, and lifecycle-spanning data, providing an ideal foundation for the integration of AI. AI algorithms can identify patterns, predict future states, optimize complex operations, and support human decision-makers in novel ways (Rafsanjani and Nabizadeh, 2023). In particular, the emergence of foundation models such as TSNet for status prediction in digital twins (Song et al., 2025) provides a new paradigm for handling high-dimensional and dynamic network data, offering insights for cross-lifecycle intelligence of DHN. This systemic integration ensures that design parameters are optimized based on real-world maintenance logs and operational dynamics. Therefore, by acting as an enabler, AI consumes data from DT and feeds insights back into it, creating a cycle of continuous improvement and learning for the DHN system. Fig. 13 depicts a layered architecture demonstrating the integration of AI capabilities with the DHN DT paradigm. This architecture promotes modularity and clear separation of concerns, facilitating the development, deployment, and management of AI services.

Achieving cross-stage data interoperability is a key prerequisite for implementing a DT framework in DHN. Within the proposed architecture, interoperability across lifecycle stages is supported through three complementary mechanisms.

First, model-based systems engineering (MBSE) provides a unified semantic modeling structure that maintains consistency between the planning, construction, operation, and maintenance models. Second, standardized interfaces enable structured interaction among heterogeneous engineering platforms such as BIM, GIS, and SCADA systems, thereby supporting continuous lifecycle data flow and synchronization. Third, knowledge-graph-based semantic mapping technologies transform heterogeneous lifecycle datasets into machine-readable representations, enabling cross-stage decision support and closed-loop lifecycle optimization within the DT architecture.

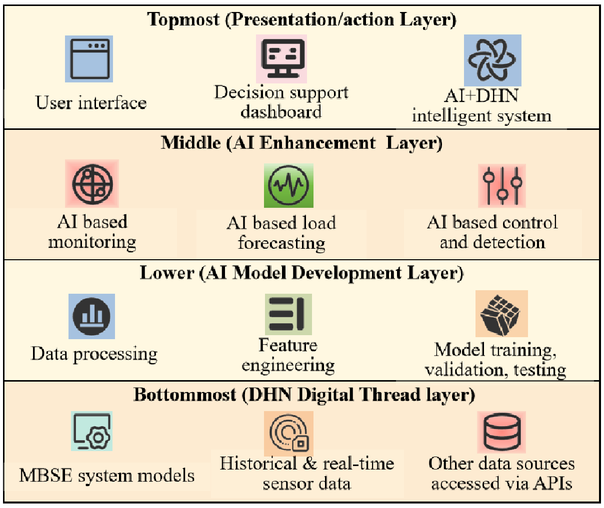

Fig. 13 A four-layer architecture of a typical AI-assisted DHN DT platform

From an organizational perspective, the proposed DT framework supports coordination between planning, construction, operation, and maintenance teams by providing a shared lifecycle data environment. Planning teams contribute system topology and design parameters through MBSE-based models, construction teams update as-built information via BIM platforms, operation teams provide real-time monitoring data through SCADA systems, and maintenance teams supply asset health records and fault diagnosis results. By integrating these heterogeneous inputs within a unified semantic framework, the DT approach enables role-oriented access to consistent system information, and supports coordinated decision-making across departments throughout the DHN lifecycle.

An AI-assisted DHN DT acts as a data flow catalyst for several key functions:

AI enables closed-loop optimization between planning/design and maintenance by extracting fault patterns and optimizing parameters based on operational data. With this knowledge, AI can automatically suggest modifications to design parameters.

AI links the optimization of construction and operations by identifying discrepancies of construction with design states, and adjusting parameters to reduce risks. AI models can adjust operational parameters based on real construction data, mapping quality issues to operational risks and automatically refining monitoring strategies and safeguards, thus reducing performance gaps and operational risks.

AI can coordinate optimization between operations and maintenance by employing algorithms that adjust strategies in response to changing conditions, consequently facilitating integrated PdM. Advanced time-series analysis and causal reasoning algorithms can be used to identify causal relationships between specific operational modes (e.g., frequent start-stop cycles, extreme temperature conditions) and degradation to the health of components. AI may also dynamically adjust maintenance strategies based on operating conditions, thus balancing component lifespan, energy efficiency, and maintenance costs.

Furthermore, knowledge graphs and semantic mapping technologies can automatically map heterogeneous data generated across various lifecycle stages (GIS, BIM, SCADA, maintenance records) to corresponding elements in a MBSE model, maintaining the consistency and integrity of the DT. This allows genuine system-level optimization based on full-lifecycle data, rather than local optima.

5.3 Outlook and future research directions

Overall, while the potential of AI for DHN transformation is immense, realizing its full benefits necessitates addressing integration challenges and embracing holistic approaches like DT. Looking ahead, several innovations are expected to further enhance AI's capability as a cross-lifecycle data flow catalyst within DHN DTs:

1) Adaptive cross-stage semantic interfaces: Future AI systems will likely develop more advanced adaptive semantic understanding capabilities, capable of automatically learning and adjusting term mappings and data transformation rules across different lifecycle stages, gradually reducing the need for manual intervention. These semantic interfaces are expected to further enhance interoperability across heterogeneous lifecycle platforms, and reduce the manual data translation effort required between engineering stages.

2) Proactive cross-stage data augmentation: Novel AI systems will likely shift from passively processing existing data to proactively identifying critical gaps in the lifecycle data flow. By using advanced causal reasoning, physical models, and

semantic reasoning techniques, they will automatically generate or infer critical missing data points and relationships, ensuring the integrity of the DT even when data collection is incomplete in certain stages.

3) Distributed collaborative AI agent networks: Instead of a single central AI system, the future may see the development of a network composed of multiple specialized AI agents, each focusing on specific lifecycle stages or specific types of cross-stage data flows. These agents may collaborate through standardized protocols to collectively maintain and optimize the entire DT. This distributed approach will enhance the system's scalability, robustness, and specialization ability.

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Author contributions

Xueru Lin and Yanhao Feng designed the research. Xu Zhou and Lingkai Zhu processed the corresponding data. Yanhao Feng, and Wenxuan Guo wrote the first draft of the manuscript. Songjie Wang and Nan Zhang revised and edited the final version. Zitao Yu helped to organize the manuscript. Wei Zhong and Xingtao Tian were responsible for funding acquisition.

Conflict of interest

Xu Zhou, Songjie Wang, Yanhao Feng, and Xueru Lin declare that they have no conflict of interest.

Declaration on the use of generative AI tools

Xu Zhou, Songjie Wang, Yanhao Feng, and Xueru Lin declare that they have not used AI-generated content; generative AI tools were used only for manuscript polishing.

Data availability

Data will be made available on request.

References

Abdar M, Pourpanah F, Hussain S, et al., 2021. A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Information Fusion*, 76:243–297. https://doi.org/10.1016/j.inffus.2021.05.008

Abioye SO, Oyedele LO, Akanbi L, et al., 2021. Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, 44 https://doi.org/10.1016/j.jobe.2021.103299

Abokersh MH, Vallès M, Cabeza LF, et al., 2020. A framework for the optimal integration of solar assisted district heating in different urban sized communities: A robust machine learning approach incorporating global sensitivity analysis. *Applied Energy*, 267 https://doi.org/10.1016/j.apenergy.2020.114903

Almatared M, Sulaiman M, Alghamdi A, et al., 2025. An artificial-intelligence-based predictive maintenance strategy using long short-term memory networks for optimizing hvac system performance in commercial buildings. *Buildings*, 15(22):4129. https://doi.org/10.3390/buildings15224129

Arce ID, López SH, Perez SL, et al., 2018. Models for fast modelling of district heating and cooling networks. *Renewable & Sustainable Energy Reviews*, 82:1863–1873. https://doi.org/10.1016/j.rser.2017.06.109

Ashtari MA, Ansari R, Hassannayebi E, et al., 2022. Cost overrun risk assessment and prediction in construction projects: A bayesian network classifier approach. *Buildings*, 12(10) https://doi.org/10.3390/buildings12101660

Baduge SK, Thilakarathna S, Perera JS, et al., 2022. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, 141 https://doi.org/10.1016/j.autcon.2022.104440

Bahlawan H, Ferraro N, Gambarotta A, et al., 2022. Detection and identification of faults in a district heating network. *Energy Conversion and Management*, 266 https://doi.org/10.1016/j.enconman.2022.115837

Bode G, Thul S, Baranski M, et al., 2020. Real-world application of machine-learning-based fault detection trained with experimental data. *Energy*, 198 https://doi.org/10.1016/j.energy.2020.117323

Boussaid T, Rousset F, Scuturici VM, et al., 2024. Enabling fast prediction of district heating networks transients via a physics-guided graph neural network. *Applied Energy*, 370 https://doi.org/10.1016/j.apenergy.2024.123634

Boutarene A, 2025. Predicting heat load in district heating systems. Independent thesis Advanced level (degree of Master (Two Years)), Stockholm University, Stockholm. http://urn.kb.se/resolve?urn=urn:nbn:se:su:diva-243705

Brown A, Foley A, Laverty D, et al., 2022. Heating and cooling networks: A comprehensive review of modelling approaches to map future directions. *Energy*, 261 https://doi.org/10.1016/j.energy.2022.125060

Buffa S, Fouladfar MH, Franchini G, et al., 2021. Advanced control and fault detection strategies for district heating and cooling systems-a review. *Applied Sciences-Basel*, 11(1) https://doi.org/10.3390/app11010455

Cademix I, 2023. Top 7 powerful ways ai and bim integration is revolutionizing the aec industry. Technical Report, https://www.cademix.org/top-7-powerful-ways-ai-and-bim-integration-is-rev/.

Castaneda M, Franco CJ, Dyner I, 2017. Evaluating the effect of technology transformation on the electricity utility industry. *Renewable & Sustainable Energy Reviews*, 80:341–351. https://doi.org/10.1016/j.rser.2017.05.179

Chan LS, 2024. Piping network optimization for district heating system using an enhanced genetic algorithm searching method. *Journal of Building Engineering*, 95 https://doi.org/10.1016/j.jobe.2024.110078

Chen K, Hu J, Yu L, et al., 2022. A data-driven model of pipe diameter and insulation thickness optimization for district heating systems. *Journal of Physics: Conference Series*, 2166(1):012046. https://doi.org/10.1088/1742-6596/2166/1/012046

Chen ZQ, Yang Y, Jiang CD, et al., 2025. Enhanced industrial heat load forecasting in district networks via a multi-scale fusion ensemble deep learning. *Expert Systems with Applications*, 272 https://doi.org/10.1016/j.eswa.2025.126783

Cheng MY, Hoang ND, Wu YW, 2015. Cash flow prediction for construction project using a novel adaptive time-dependent least squares support vector machine inference model. *Journal of Civil Engineering and Management*, 21(6):679–688. https://doi.org/10.3846/13923730.2014.893906

Choi SW, Lee EB, Kim JH, 2021. The engineering machine-learning automation platform : A big-data-driven ai tool for contractors' sustainable management solutions for plant projects. *Sustainability*, 13(18) https://doi.org/10.3390/su131810384

Çolak M, Irmak E, 2023. A state-of-the-art review on electric power systems and digital transformation. *Electric Power Components and Systems*, 51(11):1089–1112. https://doi.org/10.1080/15325008.2023.2189760

De Giuli LB, La Bella A, Scattolini R, 2024. Physics-informed neural network modeling and predictive control of district heating systems. *Ieee Transactions on Control Systems Technology*, 32(4):1182–1195. https://doi.org/10.1109/Tcst.2024.3355476

Dikmen I, Eken G, Erol H, et al., 2025a. Automated construction contract analysis for risk and responsibility assessment using natural language processing and machine learning. *Computers in Industry*, 166:104251. https://doi.org/https://doi.org/10.1016/j.compind.2025.104251

Dikmen I, Eken G, Erol H, et al., 2025b. Automated construction contract analysis for risk and responsibility assessment using natural language processing and machine learning. *Computers in Industry*, 166 https://doi.org/10.1016/j.compind.2025.104251

Dmytro K, Загальної І, України», et al., 2024. Method for assessing the efficiency of the district heating system under market conditions. *Vidnovluvana energetika*, https://doi.org/10.36296/1819-8058.2024.4(79).6-1

Dominik H, R. FM, André X, et al., 2022. Operational optimization of a 4th generation district heating network with mixed integer quadratically constrained programming. *Energy*, 250 https://doi.org/10.1016/j.Energy.2022.123766

Edirisinghe R, 2019. Digital skin of the construction site smart sensor technologies towards the future smart construction site. *Engineering Construction and Architectural Management*, 26(2):184–223. https://doi.org/10.1108/Ecam-04-2017-0066

Eia, 2024. International - u.S. Energy information administration (eia). Technical Report, U.S. Energy Information Administration, https://www.eia.gov/international/overview/world.

Elhafaia MH, Nova-Rincon A, Sochard S, et al., 2025. Optimization of the pipe diameters and the dynamic operation of a district heating network using a robust initialization strategy. *Applied Thermal Engineering*, 258 https://doi.org/10.1016/j.applthermaleng.2024.124533

Fang WL, Ding LY, Zhong BT, et al., 2018. Automated detection of workers and heavy equipment on construction sites: A convolutional neural network approach. *Advanced Engineering Informatics*, 37:139–149. https://doi.org/10.1016/j.aei.2018.05.003

Finkenrath M, Faber T, Behrens F, et al., 2022. Holistic modelling and optimisation of thermal load forecasting, heat generation and plant dispatch for a district heating network. *Energy*, 250 https://doi.org/10.1016/j.energy.2022.123666

Fu C, Liu JH, Wang SD, 2021. Building sysml model graph to support the system model reuse. *Ieee Access*, 9:132374–132389. https://doi.org/10.1109/Access.2021.3115165

Geysen D, De Somer O, Johansson C, et al., 2018. Operational thermal load forecasting in district heating networks using machine learning and expert advice. *Energy and Buildings*, 162:144–153. https://doi.org/10.1016/j.enbuild.2017.12.042

Gjoka K, Rismanchi B, Crawford RH, 2023. Fifth-generation district heating and cooling systems: A review of recent advancements and implementation barriers. *Renewable & Sustainable Energy Reviews*, 171 https://doi.org/10.1016/j.rser.2022.112997

Golparvar-Fard M, Peña-Mora F, Savarese S, 2015. Automated progress monitoring using unordered daily construction photographs and ifc-based building information models. *Journal of Computing in Civil Engineering*, 29(1) https://doi.org/10.1061/(Asce)Cp.1943-5487.0000205

Gong MJ, Zhao Y, Sun JW, et al., 2022. Load forecasting of district heating system based on informer. *Energy*, 253 https://doi.org/10.1016/j.energy.2022.124179

Gong MJ, Liu Y, Sun JW, et al., 2024. Intelligent control of district heating system based on rdpg. *Engineering Applications of Artificial Intelligence*, 129 https://doi.org/10.1016/j.engappai.2023.107672

Guelpa E, Capone M, Sciacovelli A, et al., 2023. Reduction of supply temperature in existing district heating: A review of strategies and implementations. *Energy*, 262 https://doi.org/10.1016/j.energy.2022.125363

Hanafy NO, 2025. An extensive examination of uses of machine learning and artificial intelligence in the construction industry's project life cycle. *Energy and Buildings*, 345 https://doi.org/10.1016/j.enbuild.2025.116094

Hassan MA, Serra S, Sochard S, et al., 2024. Holistic non-linear optimization of the layout, sizing, and operation of a district heating plant. *Energy Conversion and Management*, 301:118079–. https://doi.org/10.1016/j.Enconman.2024.118079

Idowu S, Saguna S, Åhlund C, et al., 2016. Applied machine learning: Forecasting heat load in district heating system. *Energy and Buildings*, 133:478–488. https://doi.org/10.1016/j.enbuild.2016.09.068

Iea, 2025. Renewables 2025 - renewable heat. Technical Report, IEA, Paris. https://www.iea.org/reports/renewables-2025/renewable-heat.

Ise, 2024. Ai-controlled heat pumps increase efficiency. Technical Report, https://www.ise.fraunhofer.de/en/press-media/press-releases/2024/ai-controlled-heat-pumps-increase-efficiency.html.

Jebamalai JM, Marlein K, Laverge J, 2020. Influence of centralized and distributed thermal energy storage on district heating network design. *Energy*, 202 https://doi.org/10.1016/j.energy.2020.117689

Jiang MT, Rindt C, Smeulders DMJ, 2022. Optimal planning of future district heating systems-a review. *Energies*, 15(19) https://doi.org/10.3390/en15197160

Johansen K, Werner S, 2022. Something is sustainable in the state of denmark: A review of the danish district heating sector. *Renewable & Sustainable Energy Reviews*, 158 https://doi.org/10.1016/j.rser.2022.112117

Johansen KW, Nielsen R, Schultz C, et al., 2021. Automated activity and progress analysis based on non-monotonic reasoning of construction operations. *Smart and Sustainable Built Environment*, 10(3):457–486. https://doi.org/10.1108/Sasbe-03-2021-0044

Johansson C, Bergkvist M, Geysen D, et al., 2017. Operational demand forecasting in district heating systems using ensembles of online machine learning algorithms. *15th International Symposium on District Heating and Cooling (Dhc15-2016)*, 116:208–216. https://doi.org/10.1016/j.egypro.2017.05.068

Kayfeci M, Yabanova I, Keçebas A, 2014. The use of artificial neural network to evaluate insulation thickness and life cycle costs: Pipe insulation application. *Applied Thermal Engineering*, 63(1):370–378. https://doi.org/10.1016/j.applthermaleng.2013.11.017

Kazeem KO, Olawumi TO, Osunsanmi T, 2023. Roles of artificial intelligence and machine learning in enhancing construction processes and sustainable communities. *Buildings*, 13(8) https://doi.org/10.3390/buildings13082061

Kim S, Kim JH, Kim YS, et al., 2025. Hybrid ai chiller model using transfer learning: Aleatoric and epistemic uncertainty. *Energy & Buildings*, 341:115840–115840. https://doi.org/10.1016/j.Enbuild.2025.115840

Kleinertz B, Gruber K, 2022. District heating supply transformation e strategies, measures, and status quo of network operators' transformation phase. *Energy*, 239 https://doi.org/10.1016/j.energy.2021.122059

Kuntuarova S, Licklederer T, Huynh T, et al., 2024. Design and simulation of district heating networks: A review of modeling approaches and tools. *Energy*, 305 https://doi.org/10.1016/j.energy.2024.132189

Kurek T, Bielecki A, Swirski K, et al., 2021. Heat demand forecasting algorithm for a warsaw district heating network. *Energy*, 217 https://doi.org/10.1016/j.energy.2020.119347

Lambert J, Spliethoff H, 2024. A two-phase nonlinear optimization method for routing and sizing district heating systems. *Energy*, 302 https://doi.org/10.1016/j.energy.2024.131843

Lauenburg P, Wollerstrand J, 2014. Adaptive control of radiator systems for a lowest possible district heating return temperature. *Energy and Buildings*, 72:132–140. https://doi.org/10.1016/j.enbuild.2013.12.011

Lee D, Yoon SM, Lee J, et al., 2020. Applying deep learning to the heat production planning problem in a district heating system. *Energies*, 13(24) https://doi.org/10.3390/en13246641

Li MS, Deng WM, Xiahou KS, et al., 2020. A data-driven method for fault detection and isolation of the integrated energy-based district heating system. *Ieee Access*, 8:23787–23801. https://doi.org/10.1109/Access.2020.2970273

Lin YF, Huang CE, Li CW, et al., 2026. Interpretable multi-task dual-attention model for forecasting heating load and supply water temperature in district heating systems. *Energy and Buildings*, 352 https://doi.org/10.1016/j.enbuild.2025.116837

Lin ZH, Chen ALY, Hsieh SH, 2021. Temporal image analytics for abnormal construction activity identification. *Automation in Construction*, 124 https://doi.org/10.1016/j.autcon.2021.103572

Liu C, Zhou SJ, Zhang YL, et al., 2023. Leakage diagnosis of district heating-network based on system simulation and pca_bp neural network. *Process Safety and Environmental Protection*, 180:260–273. https://doi.org/10.1016/j.psep.2023.09.069

Losi E, Manservigi L, Spina PR, et al., 2024. Data-driven approach for the detection of faults in district heating networks. *Sustainable Energy Grids & Networks*, 38 https://doi.org/10.1016/j.segan.2024.101355

Lu S, Gao ZH, Sun Y, et al., 2024. Aggregate model of district heating network for integrated energy dispatch: A physically informed data-driven approach. *Ieee*

Transactions on Sustainable Energy, 15(3):1859–1871. https://doi.org/10.1109/Tste.2024.3383062

Luderer G, Madeddu S, Merfort L, et al., 2022. Impact of declining renewable energy costs on electrification in low-emission scenarios (vol 7, pg 32, 2022). *Nature Energy*, 7(4):380–381. https://doi.org/10.1038/s41560-022-01000-1

Lund H, Østergaard PA, Sorknæs P, et al., 2025. District heating in clean energy systems. *Nature Reviews Clean Technology*, 1(8):532–546. https://doi.org/10.1038/s44359-025-00076-8

Luo XC, Li H, Cao DP, et al., 2018. Recognizing diverse construction activities in site images via relevance networks of construction-related objects detected by convolutional neural networks. *Journal of Computing in Civil Engineering*, 32(3) https://doi.org/10.1061/(Asce)Cp.1943-5487.0000756

Lv XJ, Li MH, 2021. Application and research of the intelligent management system based on internet of things technology in the era of big data. *Mobile Information Systems*, 2021 https://doi.org/10.1155/2021/6515792

Madsen H, 2023. Artificial intelligence in district heating. Technical Report, https://dbdh.org/artificial-intelligence-in-district-heating/.

Manservigi L, Bahlawan H, Losi E, et al., 2022. A diagnostic approach for fault detection and identification in district heating networks. *Energy*, 251 https://doi.org/10.1016/j.energy.2022.123988

Marhy, 2023. Ai revolutionizes hvac maintenance: Boost efficiency & cut costs. Technical Report, https://www.marhy.com/ai-revolutionizes-hvac-maintenance-boost-efficiency-cut-costs/.

Mazzarino PR, Capone M, Guelpa E, et al., 2022. A multi-agent framework to evaluate energy flexibility in district heating networks. *2022 Ieee International Conference on Environment and Electrical Engineering and 2022 Ieee Industrial and Commercial Power Systems Europe (Eeeic / I&Cps Europe)*, https://doi.org/10.1109/Eeeic/Icpseurope54979.2022.9854622

Mbiydzenyuy G, Nowaczyk S, Knutsson H, et al., 2021. Opportunities for machine learning in district heating. *Applied Sciences-Basel*, 11(13) https://doi.org/10.3390/app11136112

Mehraj N, Mateu C, Cabeza LF, 2024. Use of artificial intelligence methods in designing thermal energy storage tanks: A bibliometric analysis. *Journal of Energy Storage*, 97 https://doi.org/10.1016/j.est.2024.112794

Meibodi SS, Loveridge F, 2022. The future role of energy geostructures in fifth generation district heating and cooling networks. *Energy*, 240 https://doi.org/10.1016/j.energy.2021.122481

Mishra S, Shinde M, Yadav A, et al., 2024. An ai-driven data mesh architecture enhancing decision-making in infrastructure construction and public procurement. https://doi.org/10.48550/arXiv.2412.00224

Mugnini A, F. F, M. L, et al., 2022. Advanced control techniques for chp-dh systems: A critical comparison of model predictive control and reinforcement learning. *Energy Conversion and Management: X*, 15 https://doi.org/10.1016/j.Ecmx.2022.100264

Ntakolia C, Anagnostis A, Moustakidis S, et al., 2022. Machine learning applied on the district heating and cooling sector: A review. *Energy Systems-Optimization Modeling Simulation and Economic Aspects*, 13(1):1–30. https://doi.org/10.1007/s12667-020-00405-9

Palasz P, Przysowa R, 2019. Using different ml algorithms and hyperparameter optimization to predict heat meters' failures. *Applied Sciences-Basel*, 9(18) https://doi.org/10.3390/app9183719

Pinto G, Deltetto D, Capozzoli A, 2021. Data-driven district energy management with surrogate models and deep reinforcement learning. *Applied Energy*, 304 https://doi.org/10.1016/j.apenergy.2021.117642

Quaggiotto D, Vivian J, Zarrella A, 2021. Management of a district heating network using model predictive control with and without thermal storage. *Optimization and Engineering*, 22(3):1897–1919. https://doi.org/10.1007/s11081-021-09644-w

Rafati A, Shaker HR, 2024. Predictive maintenance of district heating networks: A comprehensive review of methods and challenges. *Thermal Science and Engineering Progress*, 53 https://doi.org/10.1016/j.tsep.2024.102722

Rafsanjani HN, Nabizadeh AH, 2023. Towards human-centered artificial intelligence (ai) in architecture, engineering, and construction (aec) industry. *Computers in Human Behavior Reports*, 11 https://doi.org/10.1016/j.chbr.2023.100319

Rodrigue D, Mabrouk MT, Pasdeloup B, et al., 2024. Topology reduction through machine learning to accelerate dynamic simulation of district heating. *Energy and Ai*, 17 https://doi.org/10.1016/j.egyai.2024.100393

Roelofs C, Guevara E, Hugo T, et al., 2025. Enabling predictive maintenance in district heating substations: A labelled dataset and fault detection evaluation framework based on service data. https://doi.org/10.48550/arXiv.2511.14791

Saarinen L, Boman K, 2012. Optimized district heating supply temperature for large networks; optimerad framledningstemperatur foer stora fjaerrvaermenaet.

Sakkas NP, Abang R, 2022. Thermal load prediction of communal district heating systems by applying data-driven machine learning methods. *Energy Reports*, 8:1883–1895. https://doi.org/10.1016/j.egyr.2021.12.082

Sarbu I, Mirza M, Crasmareanu E, 2019. A review of modelling and optimisation techniques for district heating systems. *International Journal of Energy Research*, 43(13):6572–6598. https://doi.org/10.1002/er.4600

Schmidt J, Stange P, 2021. Optimization of district heating network design. *Energy Reports*, 7:97–104.

https://doi.org/10.1016/j.egyr.2021.09.034

Seong H, Son H, Kim C, 2018. A comparative study of machine learning classification for color-based safety vest detection on construction-site images. *Ksce Journal of Civil Engineering*, 22(11):4254–4262. https://doi.org/10.1007/s12205-017-1730-3

Seraj H, Abbaspour A, Bahadori-Jahromi A, 2025. Towards a hybrid retrofit planning framework: A data-driven tool for energy retrofit in residential buildings. *Energy and Built Environment*, https://doi.org/https://doi.org/10.1016/j.enbenv.2025.05.013

Shakeel A, Chong DT, Wang JS, 2023. Load forecasting of district heating system based on improved fb-prophet model. *Energy*, 278 https://doi.org/10.1016/j.energy.2023.127637

Shen YC, Chen JP, Fu QM, et al., 2021. Detection of district heating pipe network leakage fault using ucb arm selection method. *Buildings*, 11(7) https://doi.org/10.3390/buildings11070275

Sholeh M, Fauziyah S, Khasani R, 2020. Effect of building information modeling (bim) on reduced construction time-costs: A case study. *E3S Web of Conferences*, 202 https://doi.org/10.1051/e3sconf/202020202012

Solinas FM, Bottaccioli L, Guelpa E, et al., 2021. Peak shaving in district heating exploiting reinforcement learning and agent-based modelling. *Engineering Applications of Artificial Intelligence*, 102 https://doi.org/10.1016/j.engappai.2021.104235

Song JC, Zhang LY, Xue GX, et al., 2021. Predicting hourly heating load in a district heating system based on a hybrid cnn-lstm model. *Energy and Buildings*, 243 https://doi.org/10.1016/j.enbuild.2021.110998

Song JC, Li W, Zhu S, et al., 2024. Predicting hourly heating load in district heating system based on the hybrid bi-directional long short-term memory and temporal convolutional network model. *JOURNAL OF CLEANER PRODUCTION*, 463 https://doi.org/10.1016/j.jclepro.2024.142769

Song SY, Sun GA, Chang YF, et al., 2025. Tsnet: A foundation model for wireless network status prediction in digital twins. *Frontiers of Information Technology & Electronic Engineering*, 26(2):301–308. https://doi.org/10.1631/Fitee.2400295

Souza F, Badings T, Postma G, et al., 2025. Integrating expert and physics knowledge for modeling heat load in district heating systems. *Ieee Transactions on Industrial Informatics*, 21(5):3955–3965. https://doi.org/10.1109/Tii.2025.3534419

Su LQ, Nie T, Ho CO, et al., 2022. Optimizing pipe network design and central plant positioning of district heating and cooling system: A graph-based multi-objective genetic algorithm approach. *Applied Energy*, 325 https://doi.org/10.1016/j.apenergy.2022.119844

Sun Z, Yao QW, Shi L, et al., 2025. Virtual sample diffusion generation method guided by large language model-generated knowledge for enhancing information completeness and zero-shot fault diagnosis in building thermal systems. *Journal of Zhejiang University-Science A*, 26(10):895 – 916. https://doi.org/10.1631/jzus.A2400560

Terhan M, 2022. Optimization insulation thickness and reduction of co2 emissions for pipes in all generation district heating networks. *Science Progress*, 105(3):00368504221122287. https://doi.org/10.1177/00368504221122287

Upasane SJ, Hagras H, Anisi MH, et al., 2024. A type-2 fuzzy-based explainable ai system for predictive maintenance within the water pumping industry. *IEEE Transactions on Artificial Intelligence*, 5(2):490–504. https://doi.org/10.1109/TAI.2023.3279808

Urbanucci L, D'ettorre F, Testi D, 2019. A comprehensive methodology for the integrated optimal sizing and operation of cogeneration systems with thermal energy storage. *Energies*, 12(5) https://doi.org/10.3390/en12050875

Van Dreven J, Cheddad A, Alawadi S, et al., 2025. From data scarcity to diagnostic precision: A novel data augmentation and fault diagnosis framework for district heating substations. *Engineering Applications of Artificial Intelligence*, 151 https://doi.org/10.1016/j.engappai.2025.110662

Vollmer E, Ruck J, Volk R, et al., 2025. Leak detection using thermal imagery: Deep learning versus traditional computer vision state-of-the-art. *Isprs Journal of Photogrammetry and Remote Sensing*, 228:505–518. https://doi.org/10.1016/j.isprsjprs.2025.06.006

Wang HN, He QQ, Zhang Z, et al., 2021a. Framework of automated value stream mapping for lean production under the industry 4.0 paradigm. *Journal of Zhejiang University-Science A*, 22(5):382–395. https://doi.org/10.1631/jzus.A2000480

Wang JD, Zhou ZG, Zhao JN, et al., 2019. Optimizing for clean-heating improvements in a district energy system with high penetration of wind power. *Energy*, 175:1085–1099. https://doi.org/10.1016/j.energy.2019.03.153

Wang LJ, Zhao J, Xu ZH, et al., 2023a. Integrated energy system optimal operation using data-driven district heating network model. *Energy and Buildings*, 291 https://doi.org/10.1016/j.enbuild.2023.113100

Wang RH, Jie PF, Wang DL, et al., 2021b. Optimization of insulation thickness of double buried district heating pipes using the eco-indicator method. *Journal of Building Engineering*, 41 https://doi.org/10.1016/j.jobe.2021.102393

Wang ZJ, Liu XF, Huang YH, et al., 2023b. A multivariate time series graph neural network for district heat load forecasting. *Energy*, 278 https://doi.org/10.1016/j.energy.2023.127911

Wei ZC, Tien PW, Calautit J, et al., 2024. Investigation of a model predictive control (mpc) strategy for seasonal thermochemical energy storage systems in district heating networks. *Applied Energy*, 376 https://doi.org/10.1016/j.apenergy.2024.124164

Woźniak Z, Trybuszewski K, Nowobilski T, et al., 2025. Integrated construction-site hazard detection system using ai algorithms in support of sustainable occupational safety management. *Sustainability*, 17(23):10584. https://doi.org/10.3390/su172310584

Wu D, Zhang YQ, Liu B, et al., 2024. Optimization of coal power phaseout pathways ensuring energy security: Evidence from shandong, china's largest coal power province. *Energy Policy*, 192 https://doi.org/10.1016/j.enpol.2024.114180

Wu JJ, Zhuang DY, Bian XC, et al., 2025. Preliminary study on evaluation indicators for urban engineering system sustainability. *Journal of Zhejiang University-Science A*, 26(12):1229–1243. https://doi.org/10.1631/jzus.A2400522

Xi F, Liu LY, Shan LY, et al., 2024. Pipeline leak identification and prediction of urban water supply network system with deep learning artificial neural network. *Water*, 16(20) https://doi.org/10.3390/w16202903

Xu H, Zhang L, Wang XB, et al., 2024. Improved genetic algorithm for pipe diameter optimization of an existing large-scale district heating network. *Energy*, 304 https://doi.org/10.1016/j.energy.2024.131970

Xu ZY, Saleh JH, 2021. Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. *Reliability Engineering & System Safety*, 211 https://doi.org/10.1016/j.ress.2021.107530

Xue PN, Jiang Y, Zhou ZG, et al., 2019. Multi-step ahead forecasting of heat load in district heating systems using machine learning algorithms. *Energy*, 188 https://doi.org/10.1016/j.energy.2019.116085

Xue PN, Jiang Y, Zhou ZG, et al., 2020. Machine learning-based leakage fault detection for district heating networks. *Energy and Buildings*, 223 https://doi.org/10.1016/j.enbuild.2020.110161

Yan YM, Liang YT, Zhang HR, et al., 2019. A two-stage optimization method for unmanned aerial vehicle inspection of an oil and gas pipeline network. *Petroleum Science*, 16(2):458–468. https://doi.org/10.1007/s12182-019-0305-y

Yang G, Xing DH, Wang H, 2024. Leak localization in district heating networks integrating physical model-based and data driven-based methods: Impact of dataset construction on model performance. *Energy*, 308 https://doi.org/10.1016/j.energy.2024.132839

Yau N-J, Yang J-B, 1998. Case - based reasoning in construction management. *Computer - Aided Civil and Infrastructure Engineering*, 13 https://doi.org/10.1111/0885-9507.00094

Zdravkovic M, Ciric I, Ignjatovic M, 2022. Explainable heat demand forecasting for the novel control strategies of district heating systems. *Annual Reviews in Control*, 53:405–413. https://doi.org/10.1016/j.arcontrol.2022.03.009

Zhang Q, Liu JH, Chen X, 2024a. A literature review of the digital thread: Definition, key technologies, and applications. *Systems*, 12(3) https://doi.org/10.3390/systems12030070

Zhang T, Luo J, Chen P, et al., 2019. Flow rate control in smart district heating systems using deep reinforcement learning. *ArXiv*, https://doi.org/10.48550/arXiv.1912.05313

Zhang YC, Johansson P, Kalagasidis AS, 2022. Assessment of district heating and cooling systems transition with respect to future changes in demand profiles and renewable energy supplies. *Energy Conversion and Management*, 268 https://doi.org/10.1016/j.enconman.2022.116038

Zhang YH, Liu MZ, O'neill Z, et al., 2024b. Temperature control strategies for fifth generation district heating and cooling systems: A review and case study. *Applied Energy*, 376 https://doi.org/10.1016/j.apenergy.2024.124156

Zhang YK, Gong GF, Yang HY, et al., 2024c. From tunnel boring machine to tunnel boring robot: Perspectives on intelligent shield machine and its smart operation. *Journal of Zhejiang University-Science A*, 25(5):357–381. https://doi.org/10.1631/jzus.A2300377

Zhou HY, Zhang SH, Peng JQ, et al., 2021. Informer: Beyond efficient transformer for long sequence time-series forecasting. *Thirty-Fifth Aaai Conference on Artificial Intelligence, Thirty-Third Conference on Innovative Applications of Artificial Intelligence and the Eleventh Symposium on Educational Advances in Artificial Intelligence*, 35:11106–11115. https://doi.org/10.1609/aaai.v35i12.17325

Zhou YK, Zheng SQ, Hensen JLM, 2024. Machine learning-based digital district heating/cooling with renewable integrations and advanced low-carbon transition. *Renewable & Sustainable Energy Reviews*, 199 https://doi.org/10.1016/j.rser.2024.114466

中文概要

题目：人工智能赋能区域供热系统全生命周期演进：挑战与机遇

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目的：区域供热系统正面临低碳转型、可再生能源接入、供需不确定性增强以及基础设施更新等多重挑战。本文旨在系统梳理人工智能技术在区域供热系统全生命周期中的应用现状，分析其在规划设计、施工更新、运行控制以及维护诊断等阶段的作用机制，并提出面向全生命周期数据贯通与智能决策集成的数字主线框架，以支撑下一代区域供热系统的高效、低碳和智能化演进。

创新点：1. 提出区域供热系统全生命周期人工智能应用框架，系统覆盖规划设计、施工更新、运行控制和维护诊断等关键阶段；2. 揭示现有人工智能应用中存在的阶段割裂、数据孤岛和跨阶段协同不足问题，强调全生命周期数据贯通的重要性；3. 提出数字主线与人工智能融合思路，通过统一语义模型、标准化接口和知识反馈机制，支撑区域供热系统的闭环优化与智能演进。

方法：1. 通过文献综述,系统梳理了人工智能在区域供热系统规划设计、施工更新、运行控制、维护诊断等生命周期阶段中的典型应用（图 2、图 3 和图 4）；2. 分析机器学习、深度学习、强化学习、进化算法、多智能体系统和自然语言处理等方法在负荷预测、优化设计、施工管理、运行控制和故障诊断中的作用（表 1 和图 11）；3. 构建区域供热系统数字主线与人工智能融合框架，支撑跨阶段数据贯通、知识反馈和闭环优化（图 12）。

结论：1. 人工智能可提升区域供热系统全生命周期的设计效率、施工管理水平、运行控制精度和故障诊断能力；2. 现有研究仍存在阶段割裂和数据孤岛问题，缺乏跨阶段协同与系统级优化；3. 所提数字主线框架可促进规划、施工、运行和维护之间的信息贯通，为区域供热系统低碳化、智能化演进提供支撑。

关键词：区域供热；人工智能；全生命周期；数字主线